U.S. Long-Term Earnings Outcomes by Sex, Race, Ethnicity, and Place of Birth

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Abstract

This paper is part of the Global Income Dynamics Project cross-country comparison of earnings inequality, volatility, and mobility. Using data from the U.S. Census Bureau's Longitudinal Employer-Household Dynamics (LEHD) infrastructure files we produce a uniform set of earnings statistics for the U.S. From 1998 to 2017, we find U.S. earnings inequality has increased and volatility has decreased. The combination of increased inequality and reduced volatility suggest earnings growth differs substantially across different demographic groups. We explore this further by estimating 12-year average earnings for a single cohort of age 25-54 eligible workers. Differences in labor supply (hours paid and quarters worked) are found to explain almost 90% of the variation in worker earnings, although even after controlling for labor supply substantial earnings differences across demographic groups remain unexplained. Using a quantile regression approach, we estimate counterfactual earnings distributions for each demographic group. We find that at the bottom of the earnings distribution differences in characteristics such as hours worked, geographic division, industry, and education explain almost all the earnings gap, however above the median the contribution of the differences in the returns to characteristics becomes the dominant component.

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I. Introduction

This paper is part of the Global Income Dynamics Project cross-country comparison of earnings inequality, volatility, and mobility. Using data from the U.S. Census Bureau's Longitudinal Employer-Household Dynamics (LEHD) infrastructure files from 1998 to 2017 we find U.S. earnings inequality has increased and volatility has decreased. Taken together, these two results suggest inequality differences are both larger and more persistent at the individual worker level post Great Recession than prior to the Great Recession, which leads into the second part of the paper where we document significant long-term real earnings differences both across and within sex, race, ethnicity, and place of birth demographic groups. For each demographic group, we follow a single cohort of eligible workers age 25-54 in 2004 for 12 years. Substantial differences exist across groups. Native-born Black and Hispanic/Latino male workers earn 18% to 77% less than a similar (same point in the group earnings distribution) White male over a 12-year period (including zero-earnings years).

There is a large literature that examines earnings disparities by race and sex. Altonji and Blank (1999) provide a thorough review of the early literature. Daly, Hobijn, and Pedtke (2017) provide a more recent summary of these basic trends for average wages. In the 20 years since publication of Altonji and Blank, many of the headline findings remain true. The Black/White male wage gap has barely changed over the past 4 decades and the Black/White female wage gap has widened for the past 35 years.

Bayer and Charles (2018) compare earnings levels by percentile and rank in the earnings distribution among men from 1940-2014. They find that most of the historical reduction of the Black/White earnings gap at the median during the "great compression" has now been undone. That is, the Black and White earnings gap at the median is as large now as in the 1950s with little change over time: Black male median earnings place him at 27th percentile of White distribution after the Great Recession and 24th percentile in 1940, virtually the same as our result for 2004-2015.

Most statistics on earnings inequality in the U.S. are based on household surveys. Indeed, the U.S. Census Bureau produces an annual report that documents changing trends in income and earnings inequality by demographic characteristics based on the Current Population Survey-Annual Social and Economic Supplement (CPS ASEC). See, for example, Semega et al. (2020). Complementary recent work uses administrative data to expand the literature on race and sex earnings differentials. Kopczuk, Saez, and Song (2010) use data from the Social Security Administration to look at mobility and earnings inequality in the U.S. since 1937. They find that the gender wage gap, rather than the impact of immigration or racial earnings disparities, has the important empirical relation to overall mobility measures. Gideon, Heggeness, Murray-Close, and Myers (2017) find that when data from the Social Security Administration (SSA) Detailed Earnings Record are linked with record-level CPS data, estimates of the Black/White earnings gap at the average increase. Chetty, Hendren, Jones, and Porter (2020) use federal income tax data linked to Decennial Census and American Community Survey (ACS) data to study intergenerational earnings differences. Blacks have lower rates of upward mobility and higher rates of downward mobility than whites. In comparison, White and Hispanic children have similar rates of intergenerational mobility.

What accounts for these earnings discrepancies? Cajner, Radler, Ratner, and Vidanogs (2017) find that observables such as education, age and experience have little effect in explaining differential Black/White labor market outcomes such as unemployment. They also find that the inability to increase hours worked is an important impediment to earnings growth that varies by race. Denning, Jacob, Lefgren, and vom Lehn (2019) find that at least half of the gender earnings gap can be explained by hours differences (conditioning on race) when occupation-specific tasks are considered. Chetty, Hendren, Jones, and Porter (2020) find that conditioning on parents' income, Black/White income differentials for men are entirely explained by employment and wages for men with only a small contribution from marital status, education, and wealth. This suggests that the Black/White earnings gap is driven in part by differences in job opportunities.

Our main findings from the Global Income Dynamics Project indicators show uneven earnings growth across earnings percentiles over time and an increase in earnings inequality. These patterns motivate a deeper analysis of earnings across demographic groups. To focus on these demographics, we summarize time series changes in earnings using a measure of long-term earnings that captures periods of labor market inactivity by including zero and low earnings years. We find stark disparities among workers by comparing percentiles conditional on demographic group. When compared to our reference group of native-born White Non-Hispanic male workers, we find low-earning Black and Hispanic workers face larger earnings differentials than those with higher earnings. For example, Black men at the 10th percentile earn 18 percent of corresponding White male earnings. At the 90th percentile, Black men earn 54 percent of corresponding White male earnings. Similar differences escalating by percentile of the reference distribution persist across most native- and foreign-born groups as well as gender. An interesting exception is foreign-born Black Non-Hispanic females who see smaller earnings differentials (compared to our reference group of White males) at lower earnings percentiles compared to higher earnings percentiles.

These differences in earnings across percentiles for demographic groups reflect differences in labor market participation, age, education, human capital, geography and industry of employment. A basic regression analysis explains much of these earnings gaps, however, to better understand how these factors account for differences in earnings across the earnings distribution we perform a quantile decomposition as proposed in Machado and Mata (2005). We find that most of the earnings differentials for low earners in each demographic group are due to differences in observable characteristics. For example, more than 90 percent of the earnings differentials between Black and White Non-Hispanic males below the median can be accounted for by differences in observables. A similar pattern holds for most other demographic groups. Earnings differences among higher earning workers are largely not accounted for by differences in observable characteristics. Rather, these differences are due to differences in model coefficients—or the labor market return to observable factors specific to each demographic group.

The remainder of the paper proceeds as follows. In the next section we describe the sources of earnings data used for our analysis. The third section summarizes the inequality and mobility statistics for the Global Income Dynamics Project. The fourth section looks at inequality by demographic groups, where we focus specifically on disparities in long-term earnings by sex, race, ethnicity, and place of birth. Section five concludes.

II. Data

The empirical work in this paper is based on job-level earnings information from the Longitudinal Employer-Household Dynamics (LEHD) infrastructure files, developed and maintained by the U.S. Census Bureau.[1] In the LEHD infrastructure, a "job" is the statutory employment of a worker by a statutory employer as defined by the Unemployment Insurance

[1] See Abowd et al. (2009) for a detailed summary of the construction of the LEHD infrastructure.

(UI) system in a given state. Mandated reporting of UI-covered wage and salary payments between one statutory employer and one statutory employee is governed by the state's UI system. Reporting covers private employers and state and local government. There are no self-employment earnings unless the proprietor draws a salary, which is indistinguishable from other employees in this case.

The LEHD program is based on a voluntary federal-state partnership. When a state becomes a member of the partnership, current as well as all available historical data for that state are ingested into the LEHD internal database. By 2004, LEHD data represent the complete universe of statutory jobs covered by the UI system in the United States. However, studying job-level inequality, the task for which having a complete job frame is well suited, as a proxy for person-level inequality may be misleading due to the time-varying many-to-one assignment of jobs to workers. Therefore, we use all jobs to construct person-year level annual real (deflated by the Personal Consumption Expenditures Index (PCE)) earnings files covering the period 1998-2017.[2]

It is preferable to have both a person frame that covers a known population of interest and to have a relatively high level of confidence that the persons in that population use a consistent person identifier across all jobs. To that end, we use the U.S. Census Bureau's enhanced version of SSA's master Social Security Number (SSN) database (the Numident) to create a set of "eligible" workers each year, removing annual earnings records for ineligible workers. The first eligibility condition is that a worker have an SSN that appears on the Numident; we call such SSNs "active." Second, each year an "eligible" worker must meet an additional set of conditions: age between 25 and 55 (inclusive), not reported dead, and active SSN. If the worker has reported earnings in a given year, that worker must also not have more than 12 reported employers during the year, otherwise we assume the SSN is being used by multiple persons and the annual earnings report is discarded.

We use the basic sample of eligible workers to construct two analysis samples. The first sample is used for the across country comparisons, while the second sample is used to examine long-term average earnings within the U.S. The first sample contains approximately 1.8 billion

[2] Although our sample begins prior to the complete data period we have shown in other papers that by 1998 missing state data do not significantly affect measures of inequality and volatility (Abowd, McKinney, and Zhao 2018 and McKinney and Abowd 2020).

person-year earnings records while the second sample is constructed from approximately 1.3 billion person-year records. The two analysis sample sizes differ due to:

1. Time Period: Sample 1 uses earnings from 1998-2017 while sample 2 uses earnings from 2004 to 2015.
2. State Entry and Exit: Sample 2 includes only the complete data period (2004-2015), while sample 1 includes all years from 1998 to 2017.
3. Annual Earnings Restrictions: For much of the analysis, sample 1 imposes an earnings floor equal to 260*federal minimum wage (about $1,900 2018 PCE dollars) and a ceiling imposed by winsorizing earnings at the 99.999999th quantile. Sample 2 imposes no annual earnings restrictions. Zero-earnings years are included as long as the worker is active at least one quarter during the analysis period.
4. Age Restrictions: Sample 1 includes workers each year that are age 25-55, while sample 2 includes workers who are age 25 to 54 in 2004 (age 36 to 65 in 2015) and eligible to work each year between 2004 and 2015. Sample 1 contains a representative cross-section of workers each year with worker entry and exit, while sample 2 follows the same set of workers over a 12-year period with no worker entry and exit. Workers in sample 2 may have zero earnings years, but they are still eligible to work each year (we exclude the small number of workers who die during the analysis period).
5. Real Earnings Reference Year: The real earnings reference year for sample 1 is 2018, while the reference year for sample 2 is 2010.

For sample 1 we create a longitudinal sample of persons representative of the active worker population in each year, while in sample 2 we follow a single cohort of 109 million eligible workers for 12 years.[3] In sample 2 our focus is on the long-term earnings of a fixed set of eligible workers, including the impact on long-term earnings of periods of inactivity, while in sample 1 we concentrate on changes in earnings over time for the population of workers active each year. Given the different research focus of each sample, we create multiple measures of earnings. In sample 1 we create four measures of earnings; one measure based on annual earnings, two measures of permanent earnings and one measure of age-adjusted annual earnings.

[3] See Appendix Table A1 to see the evolution of age by year for sample 2.

Real annual earnings are the sum of real earnings e_{ijt} across all eligible employers j during the year t for a given person i subject to a minimum earnings level $m_t^* = 260 * minwage_t$

$$y_{it} = \left(\sum_j e_{ijt} \,\middle|\, \sum_j e_{ijt} > m_t^*\right).$$

The first permanent earnings measure P_{it} is defined as the average of the current and the previous two years of earnings, including zeroes and values below the minimum earnings cutoff if at least two years are above the minimum earnings cutoff

$$P_{it} = \left(\frac{(\sum_j e_{ijt-2} + \sum_j e_{ijt-1} + \sum_j e_{ijt})}{3} \,\middle|\, \begin{array}{c} I\left(\sum_j e_{ijt-2} > m_t^*\right) + I\left(\sum_j e_{ijt-1} > m_t^*\right) + \\ I\left(\sum_j e_{ijt} > m_t^*\right) \geq 2 \end{array}\right).$$

The second permanent earnings measure P_{3it} is also a three-year average earnings measure, but the timing differs and there is no minimum earnings cutoff

$$P_{3it} = \frac{(\sum_j e_{ijt-1} + \sum_j e_{ijt} + \sum_j e_{ijt+1})}{3}.$$

The final earnings measure created for sample 1 is age-adjusted log real annual earnings ε_{it}. ε_{it} is the residual from a regression of y_{it} on a set of age indicator variables by sex and year.

In contrast with sample 1, for sample 2 we only create a single earnings measure to use as a dependent variable, average real annual earnings over all years and all employers

$$w_i = \frac{1}{12} \sum_{t=2004}^{2015} \sum_j e_{ijt}.$$

We use sample 2 to explore the difference in w_i across 20 demographic categories based on sex, race, ethnicity, and place of birth. Specifically, we define these categories as the interaction of place of birth (native-born, foreign-born), sex (male, female) and race/ethnicity. The race/ethnicity variable is constructed from the following categories: Asian Non-Hispanic, Black Non-Hispanic, White Hispanic, White Non-Hispanic, and All Other race/ethnicity groups.

Hours of work and education are two potentially important predictors of average annual earnings. Although information on hours of work and education are not available for the entire population, we assume the data are missing at random in the sense of Little and Rubin (2002) and impute the missing observations conditional on all observed data. Hours are imputed using information from the small subset of states (WA, OR, RI, and MN) for whom hours data are reported. We estimate a least-squares regression model of log hours of log annual work hours at a given job as a function of log earnings quartic, age quartic, race indicators, a foreign-born indicator, and NAICS 2017 industry sector indictors. If the worker has multiple jobs during the year, then earnings at all other jobs is included as an additional covariate. The imputation regression model is estimated separately for workers with different quarterly work patterns, dominant jobs, coincident jobs, and sex.

Missing education is imputed (~80% missing) using information about a person's observed characteristics (sex, place of birth, age, race, and ethnicity) as well as the characteristics of a person's job history such as the average earnings, modal industry, and characteristics of a person's co-workers and co-residents. The characteristics are used to form homogeneous cells of a minimum size within which the distribution of observed education values is used to impute missing education values.[4]

Although education provides important information about worker skill, a much broader estimate of worker skill can be formed using the level and pattern of worker earnings over time. For example, workers with higher education levels should have relatively high earnings at all their employers compared with similar workers with less education. We estimate an AKM (Abowd, Kramarz, Margolis 1999) style earnings regression to recover the fixed person effect and the average firm effect for all workers in our analysis sample. The AKM estimation to recover these fixed person and worker effects uses all 4.4 billion job-year earnings observations in the 1990 to 2015 LEHD infrastructure files. The long time period used in the estimation allows us to observe and control for the impact of all observed co-workers when estimating our analysis sample fixed person and person average fixed firm effects.

III. Cross-Country Comparisons

III.a. Inequality

In this section we present results for the U.S. estimated using a common set of programs provided to each of the participating countries. The goal here is to produce similar estimates,

[4] McKinney et al. (2020) show that the missing at random assumption holds for education and that this method of imputation is reliable.

thus facilitating cross-country comparisons. We start by using sample 1 to estimate the change in cross-sectional earnings inequality for log real annual earnings y_{it} over time as shown in Figure 1. The y-axis shows the difference in log real annual earnings between the current year and the base year (1998) multiplied by 100. For example, using Figure 1 we see that real earnings growth for the 90th percentile from 1998 to 2017 was approximately 21 percent. Real annual earnings growth for the other percentiles was also positive except for a short period from 2003-2007 for the 5th percentile. Workers at the 90th percentile and above generally received consistent earnings increases over the entire analysis period with slower increases during the recovery from the great recession. Workers at the 50th percentile and above generally experienced real earnings growth until the Great Recession, however the recovery from the Great Recession was uneven. Workers at the 75th percentile had little or no real earnings growth from 2007 to 2013, while real earnings growth for workers at the median fell during the same period. Post 2013, real earnings growth accelerates for all workers, but the stagnant earnings of workers in the middle (50th) to the upper middle (75th) part of the earnings distribution increased earnings inequality for this group.

Workers below the median faced a roller-coaster ride. Workers at the very bottom (5th and 10th percentiles) saw real earnings decline from 2001 to 2007 with a recovery to 2001 levels by 2013. Real earnings growth in the bottom half of the earnings distribution then continued through the end of the analysis period, stemming increases in earnings inequality. Overall, earnings inequality reached a peak in 2009 and, due to the relatively strong real earnings growth at the bottom of the earnings distribution, earnings inequality has been relatively stable from that point forward.

While annual earnings are representative for most workers with stable employment, annual earnings potentially provide a misleading picture of earnings inequality for workers with less stable work histories. This is especially true if negative earnings shocks and periods of inactivity are not distributed equally across the earnings distribution. In Figure 2, we present a chart similar to Figure 1 except that in Figure 2 we show the change in the earnings distribution for P_{it}. Although the composition of the sample is somewhat different than the annual earnings sample (workers must have earnings above the cutoff in two of the three years not every year), inequality increases significantly more over the period when we use this measure of permanent rather than annual real earnings. Workers above the 90th percentile have consistent permanent earnings growth over the period, similar to our result using annual earnings. However, the pattern changes at the 75th percentile with real permanent earnings declining from 2009 forward unlike with real annual earnings where the 75th percentile is stagnant until 2013 and then shows strong growth through the end of the sample period. The decline in permanent real earnings is even larger as we move down the permanent real earnings distribution with workers at the 50th and 25th percentiles facing substantially larger declines in permanent real earnings. Overall permanent earnings inequality increased substantially over the sample period, suggesting that negative earnings shocks increasingly impacted workers in the bottom three-quarters of the earnings distribution, making the decline in permanent real earnings exceptionally broad.

Figures 3 and 4 show the ratio of the 90th to the 10th percentile for annual and permanent earnings, respectively, and largely confirm the results shown in the first two figures. Annual real earnings inequality increased until 2007 and then was largely stable or showed a small decline to the end of the analysis period. However, the 90-10 ratio for permanent real earnings shows a consistent increase in earnings inequality over the entire analysis period except for 2009. The starkly different results for permanent earnings as compared to annual earning highlight the importance of having longitudinal earnings data and allowing for zero-earnings years.

III.b. Volatility

In contrast to measuring the dispersion in earnings, as we did in the previous section, volatility measures the dispersion in the change in earnings. Dispersion of the change in earnings captures the extent to which workers face similar year-to-year earnings shocks. Figure 5 shows the 90-10 ratio (multiplied by 100) of the difference in the earnings residuals between the subsequent and current years. Previous research using more standard measures of volatility, either the variance of the difference in log earnings or the variance of the arc-percentage change, show similar results (McKinney and Abowd 2020). Dispersion is generally falling over the analysis period, except during recessions, with a relatively small increase at the end of the analysis period. Workers in 2017 generally have less dispersion in the change in earnings than workers in 1998, a result that is consistent with previous research showing workers have fewer job changes (Davis and Haltiwanger 2014).

Figure 6 shows the dispersion in volatility for workers at different points in the permanent earnings distribution. First, the support of the permanent earnings distribution is divided into 41 consecutive non-overlapping bins, with each bin representing approximately 2.5% of the earnings observations. The y-axis shows the 90-10 ratio for all the workers in each bin, separated into three different age categories. Figure 6 shows a large decline in earnings volatility as we move up the earnings distribution, except at the very top. When constructing measures of volatility using log earnings, volatility is generally greater for workers at the bottom of the earnings distribution. Large percentage changes in earnings are more likely when the level of earnings is low (someone earnings $10,000 dollars per year can more easily double their earnings than someone earning $100,000 per year). However, comparing across age groups for workers at similar points in the earnings distribution we see that, except for at the very top of the earnings distribution, younger workers generally have more volatility than older workers. It is important to keep in mind that the measures of volatility shown here use log earnings; therefore, transitions into and out of active status are not captured. Many workers have significant periods of inactivity, and a large part of volatility is due to worker entry/exit (McKinney and Abowd 2020).

III.c. Mobility

In Figures 7 and 8 we show estimates of long-term earnings mobility, comparing a worker's permanent earnings (P_{3it}) rank in the year 2000 with their earnings rank in 2005 and 2010. Both figures imply that earnings converge to the mean. Workers with a relatively high earnings rank in the first period tend to have a lower earnings rank in the future. However, we should keep in mind that these figures show changes in the ranks, not necessarily changes in permanent real earnings. A worker's rank may change because of changes in the worker's permanent real earnings and/or changes in the real permanent earnings of other workers. An additional factor to consider is that the age of the worker varies systematically across the bins of the earnings distribution in the initial period (year 2000). Younger workers are more likely to be at the bottom of the earnings distribution, while older workers are more likely to be at the top of the earnings distribution, opening the possibility that the Figures 7 and 8 simply represent lifecycle effects. In the next revision of the Global Income Dynamics Project, we plan to condition on age, thus comparing workers at similar points in the earnings lifecycle. This will potentially give a clearer picture as to whether similar age workers at the bottom of the earnings distribution in t are more likely to change ranks in $t + s$ than similar age workers at the top of the earnings distribution.

IV. Long-Term Average Earnings

The main goal of this section is to study long-term average earnings differentials across demographic groups. For this analysis we use sample 2 to follow a cohort of prime age workers, who are 25-54 years old in 2004. We monitor these workers for 12 years, observing earnings during periods of UI-covered formal labor market activity.[5] Labor force attachment varies significantly across prime age workers, although earnings differences persist even when we control for hours of work and years of inactivity. A key aspect of sample 2 is that it contains zero- and low-earnings years compared to much of the analysis conducted in Section III, which includes only years with earnings above a time-varying minimum earnings floor. Including periods of inactivity allows us to capture earnings observations in sample 2 that result from changes in labor supply along both the intensive and the extensive margin. In Figure 9 we plot the share of workers active in the labor market for three different age groups. The age groups are defined as follows; age group 1 workers have ages 25-34 in 2004, age group 2 workers are 35-44 in 2004, and age group 3 is made up of workers with ages 45-54 in 2004. At the beginning of our time series the vast majority (82-85 percent) of workers are active in all three age groups, however at the onset of the 2007-2009 recession labor market activity decreases substantially to 77-78 percent uniformly across all the age groups. During the recovery from the Great Recession we begin to see heterogeneity emerge. Strikingly, during the recovery, neither of the two younger age cohorts begin to approach the levels of labor market activity observed before the Great Recession. Activity increases slightly for the youngest age cohort, while activity continues to decline for the middle age cohort. As expected, labor market activity for older workers continues to decline although the slope of the decline post Great Recession is likely due to both the differential effects of the recovery on older workers and retirement decisions.

Using only active earners produces the log earnings profiles by age group shown in Figure 10. All three age cohorts have earnings growth before the 2007-2009 recession with the

[5] Although inactivity plays an important role in this paper, like most administrative earnings datasets the LEHD data does not contain a direct report of inactivity. Our periods of inactivity are defined by not observing UI-covered activity. Although LEHD coverage of the formal labor market is exceptionally broad, informal labor earnings, self-employment, and federal workers are not covered, and activity in these sectors may appear as periods of inactivity in our analysis dataset.

steepest growth observed by the youngest group, although the 2007-2009 recession brought small declines in average earnings across all age groups. Workers in the oldest age group had the largest decreases in earnings with slow and persistent earnings declines that continued in the subsequent economic recovery. Workers in the bottom two age groups had earnings growth starting at the beginning of the post-recession recovery, with the steepest growth observed for the youngest age group.

IV.a. Characteristics of Long-term Earnings

In the previous section we documented the changes in labor market activity and earnings for workers in sample 2. In this section, we focus on average annual earnings w_i which summarizes the impact of changes in labor supply and earnings. Our focus here is on the distribution of average real (deflated by the 2010 PCE) annual earnings w_i both within and across twenty sex, race, ethnicity, and place of birth demographic groups. For each group, Tables 1A and 1B show the 10th, 25th, 50th, 75th and 90th average real earnings percentiles. For average real earnings we show the actual percentile while for the other earnings and activity measures we show averages for workers with earnings in the neighborhood of the reported percentile. We sorted all workers by the value of their average annual earnings. The amount shown in the column "Average Annual Earnings" is the percentile of this distribution. We then used this sort order to compute average values of the other variables for workers at the indicated percentile. These averages use a window of the percentile plus or minus one percentile point. For example, the "Share of Active Each 4 Year Period" for Asian Non-Hispanic Foreign-born Females shown as 0.06 in the table is the average value for all such women whose average annual earnings are between the 9th and the 11th percentile in the distribution of average annual earnings for Asian non-Hispanic foreign-born females.

In Table 2A and 2B we expand the set of characteristics to include geography (Census division), industry, age, and education.[6] Each of these tables is grouped into a part A and part B, with part A containing statistics for the foreign-born and part B containing statistics for natives. Figure 11 illustrates the relative average annual earnings differences between each demographic group and our reference group (native-born White Non-Hispanic males) at each of the reported own-group percentiles.

[6] See Appendix Table A2 for the definitions of the geography and industry variables. Figure A1 provides a map of the Census divisions.

Before we discuss the differences in average annual earnings across demographic groups, we would like to emphasize a key point of Table 1A and 1B. Our analysis of average annual earnings compactly captures much of the earnings dynamics and variation in labor market activity across percentiles. That is, we can learn much about the earnings history of workers by looking at their percentiles in the average annual earnings distribution. To illustrate this idea, we define labor market activity by dividing our 12-year analysis period into three consecutive non-overlapping 4-year sub-periods. A worker is considered long-term active if they have at least one quarter of positive earnings in each 4-year period. Even using this weak measure of labor market attachment, average annual earnings capture much of the variation in labor market activity across percentiles. If we look at average annual earnings growth between the first and the last 4-year sub-period for workers active in each 4-year sub-period, we see a strong positive correlation across percentiles. Workers at the top of the earnings distribution have noticeably more earnings growth than workers at the bottom. Workers at the top of the earnings distribution also have lower earnings volatility, more hours worked, and fewer years of inactivity. Simply knowing a worker's long-term average annual earnings conveys a large amount of information about a worker's earning dynamics and work history.

The reference group for our comparative analysis of earnings differences is native-born White Non-Hispanic males, making it natural to start our discussion of the tables with this group. In Table 1B, native White Non-Hispanic males have reported average earnings of $3,469 at the 10th percentile. These numbers increase steadily to $38,960 at the median and to $110,400 at the 90th percentile. In comparison, native Black Non-Hispanic males have substantially lower earnings at all percentiles. For example, at the 10th percentile, we observe annual earnings of only $617. This represents only 18 percent of the earnings found for a similarly situated worker in the reference group. Figure 11 facilitates these types of comparisons, showing the ratio of average real annual earnings for all groups relative to native-born White Non-Hispanic males.

Alternatively, for groups with large earnings differences, it is useful to compare average annual earnings across percentiles. For example, the 25th percentile of the Black distribution is comparable to the 10th percentile of the White distribution with Black workers earnings $3,927 (compared to $3,469 for White workers) with similar results for hours worked with 820 hours paid (compared to 887 hours paid for White workers). Median average earnings for Black workers are $16,780, which represents 43 percent of White median earnings. At the 90th

percentile, average long-term earnings are $59,180 for Black workers. That is, at the 90th percentile of the earnings distribution Black workers earnings are less than the 75th percentile of the White distribution with more hours paid than White workers at the 90th percentile. In contrast, native-born Asian Non-Hispanic males earn more than White Non-Hispanic males at all percentiles of the earnings distribution. The relative earnings of Hispanic and the All Other race/ethnicity group fits between Black and White workers with White Hispanic workers having higher earnings than the All Other race/ethnicity group at every percentile.

Foreign-born males have more mixed outcomes by race and ethnicity. Figure 11 panel shows that while foreign-born Black Non-Hispanic males have large earnings differentials compared to of the native-born White Non-Hispanic male reference group, these differentials are smaller than those observed for foreign-born White (both Hispanic and Non-Hispanic) workers and the All Other race/ethnicity group. At higher percentiles, earnings for foreign-born White Non-Hispanic males and foreign-born Asian Non-Hispanic males exceed those of native-born White Non-Hispanic males with an earnings differential of 15-20 percent at the 90th percentile.

By sex, Table 1B shows that native White Non-Hispanic females earn $1,727 at the 10th percentile, increasing to $23,790 at the median, and $69,010 at the 90th percentile. The earnings among females of this group are lower than comparable percentile calculations for males as seen in Figure 11 panel (c). The earnings differences are even more stark among the Black and All Other groups of native females at the 10th and 25th percentiles. Native-born Black females earn $1,208 and $6,807 and the All Other group females earn $843 and $4,946 at the 10th and 25th percentiles, respectively. Asian Non-Hispanic females earn slightly less than White Non-Hispanic males at each percentile, except the 75th percentile where they slightly exceed male earnings.

Among foreign-born Black Non-Hispanic females, we find smaller earnings differentials relative to native-born White Non-Hispanic males at lower earnings percentiles than those recorded for native Black Non-Hispanic females, as described in the previous paragraph. Earnings among Black Non-Hispanic females are $2,585 at the 10th percentile and $10,920 at the 25th percentile. However, these represent only 75 and 67 percent of respective earnings among the reference group of native White Non-Hispanic males as seen in Figure 11 panel (a). Earnings among foreign-born Black Non-Hispanic females exceed the earnings of the All Other race/ethnicity group at the 10^{th}, 25^{th}, and 50^{th} percentiles. Earnings of foreign-born Asian and White females exceed those of Black females only at the 75^{th} and 90^{th} percentiles.

In Tables 2A and 2B we show the variation among demographic groups by education, geography and industry across percentiles. Low earners in each demographic group tend to be younger and less educated than higher earning workers. There is also substantial variation in education across these groups. The share of Asian workers (of any gender and place-of-birth) with a BA degree or higher at the 90^{th} percentile exceeds 70 percent. In contrast, only 14 percent of foreign-born White Hispanic workers have a BA degree or higher. There are differences in industry composition across percentiles for each demographic group. For example, workers in the 10^{th} percentile of this demographic group are usually employed in industry sectors: construction (D), retail trade (G), administrative and support (N), and manufacturing (E). At the 90^{th} percentile, only manufacturing is found in common with the workers at the 10^{th} percentile. Workers at the 90^{th} percentile are most often found in professional, technical, and scientific services (L), wholesale trade (F), and finance and insurance (J). At the 90^{th} percentile, these industries account for 51 percent of employment. Geography varies as well with low earners at the 10^{th} percentile found in the South Atlantic and East North Central Census Divisions and high earners at the 90^{th} percentile found in the East North Central and Middle Atlantic Census Divisions.

Education differences are only one measure of skill differentials. We can also use AKM-style fixed person and firm effects to provide an alternative description of the types of workers at each percentile in terms of their portable earnings component and the type of firms with which they match. In Tables 1A and 1B we detail the average fixed person and firm effects for each percentile of each demographic group. We generally find higher ability workers correspond to higher earnings percentiles, although the pattern is not monotone at the lower percentiles. For example, workers at the 10^{th} percentile often have a larger person effect than those found at the 25^{th} percentile. Workers with higher earnings are often found in high-paying firms. This is true at higher earnings percentiles for all groups. However, foreign-born Asian workers at the 10^{th} percentile of the average annual earnings distribution match with slightly better firms than those found at the 25^{th} percentile. We explore the role of these factors in the following section. Differences in observables for other demographic groups not specifically discussed in the text are detailed in Table 1A and 1B.

IV.b. Least Squares Adjusted Average Earnings Differentials

Although the unadjusted average earnings differentials across groups are large, observable characteristics associated with each worker may account for most of the observed differences. To control for differences in observable characteristics our first approach is to estimate an OLS regression. We estimate the following pooled earnings model:

$$\log{(w_i)} = \gamma_g + x_i\delta + \varepsilon_{i.}$$

We regress real average annual earnings w_i on γ_g, an indicator variable for each of our 20 demographic groups of interest ($g = 0, \ldots, 19$), and x_i a vector of covariates including an hours-worked quartic, years of inactivity, years of partial activity, division indicators, industry indicators, initial age, education indicators, fixed person effects, and average (over all employers for *i*) fixed firm effects. We begin with a minimal specification and add additional explanatory variables with each successive model. The results are presented in Table 3.

Model 1 in Table 3 shows the unconditional log average earnings differentials using native-born White Non-Hispanic males as the reference group ($g = 0$). The coefficients for model 1 are the same as the unadjusted average earnings differentials from Table 1A and Table 1B except that the differences are now shown in log points not dollars $\left(\log(w_g) - \log(w_0)\right)$. Relative to the reference group, native-born Black Non-Hispanic males have average earnings lower by just over 1 log point, which is equal to approximately $16,700. In contrast, native-born White Non-Hispanic females have earnings that are lower by 0.54 log points, almost half as small as for native-born Black Non-Hispanic males. As we add covariates, these differences decrease substantially but do not disappear. For example, in Model 5 the average earnings of native-born Black Non-Hispanics males is 0.32 log points lower than for the reference White males. The adjusted earnings differences for females are also smaller, but do not completely disappear. For example, the full model specification finds that earnings for native-born White Non-Hispanic females is -0.14 log points lower than for males.

The addition of AKM human capital variables has a notable effect on earnings differences. The addition of these additional skill measures *increases* earnings differentials for Asian and Black Non-Hispanic groups relative to the reference group. That is, the indicator variable for these groups becomes more negative when comparing Model 4 and Model 5. Recall, that the AKM measures capture person-specific skills and the quality of the employer that is separate from what can be captured by the education attainment variable alone. This persistent differential captures some characteristics of the labor market that point to the possibility of additional labor market frictions (through job matching or race discrimination). Further analysis is beyond the scope of this paper, but much additional research is needed to formalize the mechanisms behind these differentials.

IV.c. Quantile Regression Adjusted Average Earnings Differentials

The richness of our data allows us to go beyond an analysis of mean real average earnings difference across groups. In this section, we investigate the magnitude of earnings differentials between demographic groups at different percentiles of the earnings distribution. Although we showed in the previous section that observable characteristics do not completely explain earnings differentials at the conditional mean, we expect that the impact of observable characteristics differs substantially across the earnings distribution.

IV.c.i. Estimation Methodology

We define the regression estimate of quantile θ for each demographic group g as $Q_\theta\ (\ln\,(w)\,|\,x(g)) = x(g)'\beta_\theta(g)$ where w represents real average annual earnings, $x(g)$ represents a vector of covariates for group g and $\beta_\theta(g)$ represents coefficients at the estimation quantile θ for workers in group g. For each demographic group g we estimate quantile regressions including the same set of regressors as in Model 4 of Table 3. Similar to our least-squares estimates, we conduct our analysis relative to the native-born White Non-Hispanic males reference group, which is indexed by $g = 0$.

Our goal is to estimate the conditional real annual earnings distribution for each group of interest and our reference group and then use the estimated coefficients to decompose earnings differences into components due to coefficients, covariates, and a residual following the methodology outlined in Machado and Mata (2005) and Albrecht et al. (2003). First, we define the observed density of log real average annual earnings corresponding to each of our groups g by $f\big(\ln\big(w(g)\big)\big)$ and the simulated average earnings density for group g as $f_w^*\big(\beta(g); x(g)\big)$. To simulate the conditional average earnings distribution for group g we start by estimating 99 separate quantile regressions, one for each quantile $\theta = 1, \ldots, 99$. Next, we take one draw from a uniform $(0,1)$ distribution for each person in group g and assign each of them a θ_i based on dividing the support of the uniform distribution into 99 equal size bins. Using the θ_i values from the previous step we calculate the predicted average earnings $\ln\big(w_i(g)\big) = x_i(g)'\hat{\beta}_{\theta_i}(g)$ for each person in group g. The resulting simulated earnings values can then be used to estimate quantiles or any other statistic of the log average earnings distribution $f_w^*(\beta(g); x(g))$. As we will show below, the power of this approach is our ability to easily simulate counterfactual average earnings distributions by replacing for example $\hat{\beta}(g)$ with $\hat{\beta}(0)$.

We define the difference in observed log average earnings for group g and our reference group at a specific quantile as $\Theta\left(f\left(\ln\left(w(g)\right)\right)\right)$- $\Theta\left(f\left(\ln\left(w(0)\right)\right)\right)$. This earnings difference can be decomposed into three components. The first component is defined as earnings differentials that arise to due differences in covariates while holding the coefficients constant at common values. The second component is the earnings difference due to changes in coefficients holding covariates fixed at common values. The third component is the residual. More formally, we define the decomposition using the following equation:

$$\Theta\left(f\left(\ln\left(w(g)\right)\right)\right) - \Theta\left(f\left(\ln\left(w(0)\right)\right)\right) =$$

$$\underbrace{\Theta\left(f_w^*(\beta(g); x(g))\right) - \Theta\left(f_w^*(\beta(g); x(0))\right)}_{Covariates} +$$

$$\underbrace{\Theta\left(f_w^*(\beta(g); x(0))\right) - \Theta\left(f_w^*(\beta(0); x(0))\right)}_{Coefficients} +$$

$$Residual.$$

In this form of the decomposition the counterfactual distribution $f_w^*(\beta(g); x(0))$ estimates the conditional earnings distribution using the covariates of the reference group 0 combined with the estimated coefficients of group g.[7] For example, using this approach we could estimate the annual earnings distribution for native-born White Non-Hispanic males using the returns to observables of native-born Black Non-Hispanic females. Comparing this earnings distribution with the predicted earnings distribution for native-born White Non-Hispanic males reveals the change in earnings if White workers received the same returns to their observable characteristics as Black workers. The estimates of the individual components for both forms of the

[7] Alternatively, we can express the decomposition as $\Theta\left(f\left(\ln\left(w(g)\right)\right)\right) - \Theta\left(f\left(\ln\left(w(0)\right)\right)\right) = \Theta\left(f_w^*(\beta(g); x(g))\right) - \Theta\left(f_w^*(\beta(0); x(g))\right) + \Theta\left(f_w^*(\beta(0); x(g))\right) - \Theta\left(f_w^*(\beta(0); x(0))\right) + Residual.$

decomposition are shown in Tables 4A and 4B. The decompositions themselves are shown in Tables 5A and 5B.

IV.c.ii. Results

As we know from the OLS results, log real average earnings differentials exist across all groups. As we show below, the role of the coefficient and covariate components varies across both groups and percentiles of the earnings distribution within each group as seen in Tables 5A and 5B. We plot the components of the decomposition for each demographic group in Figures 12-16.

To focus the discussion, we first present results from the decomposition for native-born male Black-White earnings in Figure 15 (b). Figure 15 (b) presents a visualization of the results of the earnings decomposition between Black and White native-born Non-Hispanic males in Tables 4B and 5B. As shown previous sections, there are striking differences in earnings between Black and White workers throughout the distribution. The decomposition illustrated in Figure 15 (b) shows that much of the differential at the lower percentiles of the earnings distribution is due to the covariate component rather than coefficient component. For example, more than 90 percent of the earnings differentials predicted by our model between Black and White Non-Hispanic males below the median can be accounted for by difference in observables that make up the covariate component. As we move up the earnings distribution, the earnings differential generally decreases and the relative contribution of the covariate component decreases. At the 75th percentile, the contribution of the coefficient component begins to exceed that of the covariate component and continues to increase among workers in the higher percentiles of the earnings distribution.

Although the differences are smaller and more uniform across the earnings distribution, a similar pattern holds for native-born White Hispanic males in Figure 15 (c). Covariate differences also account for most of the earnings discrepancy between White and Asian males (Figure 15 (a)) at the bottom of the earnings distribution, although native-born Asian Non-Hispanic males actually have higher earnings than workers in the reference group. Note that because our results are relative to the reference group, Figure 15 (d) shows no difference relative to itself. We should also note that our quantile regressions generally fit the data well with the residual component in Figures 12-16 generally very close to zero.

For ease of interpretation, we construct shares of the total predicted earnings differential attributable to the differences in coefficients and covariates. These are presented in Table 5A and 5B. The share of earnings differentials accounted for by differences in model coefficients increases as we move up the earnings distribution. However, the rate of substitution between these two components varies depending on the demographic group.

For example, using Decomposition 1 the share of the total earnings differential between native-born Hispanic and Non-Hispanic White males accounted for by the coefficient component increases from 12 percent at the 10th percentile of the earnings distribution to 67 percent at the median to a 97 percent at the 90th percentile. The share of the covariate component follows the opposite pattern, consistent with the small residual component in our regression analysis. The earnings discrepancy accounted for by the coefficient component is particularly large among high-earning Hispanic workers, with smaller levels found for other demographic categories.

At the bottom of the earnings distribution, differences in covariates play a strong role in explaining real average earnings differences. As a demographic groups increases hours worked, , finds employment in higher paying industries, and/or acquires more education, the results show that the earnings gap relative to the reference group decreases dramatically. However, as we move up the earnings distribution, differences in the returns to observables play a dominant role. This increased role of the coefficient component corresponds to a difference across groups in the return to observables such as education, hours paid, etc. For workers above the median, the path to greater real average earnings is less clear. Even if higher earning workers are employed in the same industries and have similar observable education levels, they will be faced with a significant earnings gap relative to the reference group because of the differences in their coefficients—the implicit "returns" in the labor market on the characteristics. Are workers in certain groups not employed in similar occupations within high earning industries? Is there workplace discrimination? Disentangling the determinants of the differences in the return to observables across groups is a worthwhile area of future research.

IV.c.iii. Counterfactual Earnings Differentials

Finally, we use the estimated counterfactual earnings distributions to create two figures similar in spirit to the unadjusted earnings differentials shown in Figure 11. We use the counterfactual earnings distributions $f_w^*\big(\beta(g); x(0)\big)$ and $f_w^*\big(\beta(0); x(g)\big)$ to set or adjust each groups' characteristics or coefficients to the reference group, respectively. The first counterfactual is the predicted earnings distribution of group g when observable characteristics are those of the reference group; that is, the earnings distribution of group g when we control for differences in covariates (such as education, industry, division, age, etc.). The second counterfactual is the predicted earnings distribution of group g when the "returns" to observables are those of the reference group. For both counterfactuals, the comparison group is the predicted real average earnings of the reference group, $f_w^*\big(\beta(0); x(0)\big)$. We present the counterfactual earnings differentials at each percentile of interest with reference group characteristics in Figure 17, where each point is expressed as a share of the reference group $\exp\,(\Theta(f_w^*\big(\beta(\mathrm{g}); x(0)\big))/\exp\,(\Theta(f_w^*\big(\beta(0); x(0)\big))$. Figure 18 contains counterfactual earnings differentials with reference group coefficients expressed as $\exp\,(\Theta(f_w^*\big(\beta(0); x(g)\big))/\exp\,(\Theta(f_w^*\big(\beta(0); x(0)\big))$. The elements underlying these figures are found in Table 4A and 4B.

At the lower percentiles, earnings differentials decrease and compress for all groups when we control for differences in observables as seen in Figure 17. This implies, for example, that *most* of the earnings differences we observe between native-born White and Black Non-Hispanic males are due to characteristics such as education, industry, division of employment, and age as seen in Figure 17 (d). At the 10$^{\text{th}}$ percentile of the Black earnings distribution, the earnings differential decreases to less than 10 percent when compared to the reference group of native-born White Non-Hispanic males. Much of the earnings premium we observe between Asian and White Non-Hispanic males is also due to observable differences. In contrast, earnings differentials between races at higher percentiles vary little when we control for differences in covariates. At the 90$^{\text{th}}$ percentile of the Black earnings distribution, the earnings differential increases to 37 percent when compared to the reference group.

Another way of mapping these differences is to control for differences in the "returns" to observables (the coefficients) as seen in Figure 18. In this case, earnings differentials among low earnings workers are close to their actual values in Figure 11. Again, earnings differentials in this group are due to observable factors. What about higher earners? Earnings disparities decrease among higher earning workers for the Black, Hispanic, and All Other race/ethnicity groups. This finding implies that the returns to observable differences are generally larger for Non-Hispanic White workers than for other race and ethnicity groups. It is important to note that earnings differences do not disappear among high earners even when we control for differences in coefficients or returns to observables. The starkest contrast is that of native-born Black Non-

Hispanic males where earners at the 90th percentile have earnings that are 76 percent of those of the reference group of native-born White Non-Hispanic males.

Echoing the results in previous sections, the counterfactuals from quantile regressions approach suggests much of the earnings differences observed at the lower percentiles of the earnings distribution can be attributed to differences in observable characteristics, such as hours, education, industry etc. Earnings differentials at the higher percentiles are more difficult to interpret since they primarily reflect differences in the return to the observable characteristics, not differences in those characteristics. These returns could be interpreted as prices, but they could also take the form of skills, quality of job matches, or discrimination.

V. Conclusion

From 1998 to 2017 earnings inequality in the U.S. increased while volatility decreased. Although long-term mobility ranks show regression to the mean, the U.S. also has persistent differences in earnings both within and across sex, race, ethnicity, and place of birth demographic groups. Going beyond the standard OLS log earnings regression, we show that the structure of earnings differentials relative to native-born White Non-Hispanic males differs for workers throughout the earnings distribution. At the bottom of the earnings distribution differences in earnings across groups are largely due to observable characteristics suggesting that workers at the bottom of the earnings distribution may have the clearest path to improving their position. Increasing hours worked, changing employers, and attaining additional education, while difficult in many cases, is one of the standard pathways to higher real earnings. For workers above the median, differences in the return to characteristics is the dominant component. The pathway to reducing differences in the returns to observable characteristics across demographic groups is less clear. Future research towards a better understanding of the differences in the returns to observable characteristics would be a worthwhile endeavor.

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Table 1A: Foreign-Born Earnings and Activity Measures

Race/Ethnicity	N	Percentile	Average Annual Earnings	Share Active Each 4 Year Period	Earnings Growth (Active Each 4 Year Period)	Earnings Volatility (Arc Pct Change)	Average Annual Hours Worked	Years Partially Active	Years Inactive	HC Fixed Person Effect	HC Average Firm Effect
Foreign-Born Females											
		10	$1,062	0.06	-0.08	3.24	598	1.96	9.45	0.01	-0.04
		25	$6,283	0.46	0.06	1.64	1,029	2.64	5.28	-0.05	-0.05
Asian Non-Hispanic	2,416,000	50	$21,870	0.87	0.07	0.62	1,617	1.56	1.53	-0.03	0.01
		75	$49,200	0.96	0.17	0.30	1,988	0.91	0.63	0.12	0.17
		90	$88,620	0.99	0.20	0.17	2,059	0.64	0.27	0.45	0.28
		10	$2,585	0.22	-0.24	2.56	836	2.78	7.80	0.01	-0.04
		25	$10,920	0.71	-0.07	1.30	1,238	2.89	3.25	0.00	-0.02
Black Non-Hispanic	797,000	50	$24,950	0.95	0.04	0.48	1,728	1.43	0.80	0.04	0.04
		75	$42,950	0.98	0.13	0.24	2,064	0.83	0.33	0.12	0.14
		90	$68,270	0.99	0.16	0.17	2,193	0.62	0.20	0.33	0.22
		10	$646	0.06	-0.15	3.69	429	2.02	9.72	0.00	-0.08
		25	$3,884	0.35	-0.06	2.08	844	3.13	6.31	-0.04	-0.07
White Hispanic	3,213,000	50	$12,880	0.85	0.05	0.85	1,285	2.49	1.91	-0.04	-0.06
		75	$25,170	0.97	0.08	0.33	1,771	1.05	0.54	0.00	0.00
		90	$41,470	0.98	0.11	0.21	2,048	0.70	0.33	0.08	0.10
		10	$680	0.05	-0.18	3.60	442	1.85	9.78	0.06	-0.04
		25	$4,937	0.34	0.01	1.86	919	2.56	6.25	-0.01	-0.03
White Non-Hispanic	1,935,000	50	$19,330	0.83	0.05	0.74	1,454	1.77	1.92	0.01	0.01
		75	$42,400	0.95	0.12	0.32	1,852	0.95	0.68	0.15	0.11
		90	$74,350	0.97	0.17	0.21	1,943	0.68	0.39	0.43	0.22
		10	$666	0.06	-0.15	3.72	471	1.99	9.74	-0.03	-0.07
		25	$4,315	0.37	-0.11	2.03	902	3.03	6.17	-0.08	-0.06
All Other	533,000	50	$14,840	0.87	0.02	0.78	1,412	2.15	1.71	-0.08	-0.04
		75	$29,890	0.97	0.09	0.32	1,906	1.02	0.54	-0.05	0.04
		90	$50,650	0.98	0.13	0.21	2,115	0.70	0.33	0.07	0.16
Foreign-Born Males											
		10	$1,646	0.07	-0.17	3.01	741	2.02	9.34	-0.07	-0.02
		25	$9,923	0.55	-0.07	1.44	1,240	2.73	4.54	-0.12	-0.04
Asian Non-Hispanic	2,423,000	50	$32,940	0.88	0.04	0.54	1,872	1.36	1.37	-0.07	0.06
		75	$75,270	0.95	0.20	0.30	2,079	0.89	0.68	0.24	0.24
		90	$125,700	0.98	0.23	0.17	2,097	0.58	0.32	0.53	0.38
		10	$1,509	0.10	-0.30	3.03	749	2.25	9.20	-0.05	-0.03
		25	$8,709	0.46	-0.29	1.74	1,232	3.08	5.26	-0.07	-0.02
Black Non-Hispanic	794,000	50	$25,230	0.91	-0.05	0.62	1,758	1.76	1.20	-0.06	0.01
		75	$45,790	0.97	0.11	0.27	2,151	0.92	0.43	0.03	0.10
		90	$72,960	0.98	0.17	0.19	2,226	0.67	0.29	0.21	0.23
		10	$1,197	0.07	-0.29	3.42	614	2.16	9.52	-0.15	-0.02
		25	$7,361	0.44	-0.25	1.86	1,125	3.44	5.55	-0.16	-0.02
White Hispanic	3,976,000	50	$21,470	0.90	-0.08	0.68	1,641	2.28	1.35	-0.15	-0.01
		75	$37,940	0.98	0.03	0.27	2,067	1.02	0.41	-0.09	0.05
		90	$57,890	0.98	0.08	0.17	2,258	0.63	0.25	0.04	0.12
		10	$949	0.04	-0.26	3.60	554	1.81	9.89	-0.01	-0.01
		25	$8,021	0.37	-0.14	1.80	1,165	2.71	6.03	-0.04	0.01
White Non-Hispanic	2,188,000	50	$32,190	0.85	-0.01	0.65	1,764	1.68	1.69	0.00	0.06
		75	$72,230	0.94	0.11	0.31	2,019	0.92	0.71	0.27	0.19
		90	$132,100	0.96	0.17	0.24	2,027	0.70	0.48	0.67	0.32
		10	$890	0.05	-0.24	3.72	562	1.95	9.82	-0.16	-0.03
		25	$6,139	0.36	-0.23	2.00	1,105	3.15	6.21	-0.19	-0.02
All Other	610,000	50	$20,660	0.87	-0.08	0.76	1,640	2.31	1.66	-0.18	-0.01
		75	$39,670	0.96	0.04	0.30	2,107	1.03	0.51	-0.12	0.06
		90	$65,050	0.97	0.13	0.22	2,264	0.67	0.40	0.05	0.17

Notes: Estimates are created using the 108,800,000 worker sample 2. Average annual earnings show the percentile of worker average earnings at all jobs over the 12 year sample period. All measures except average annual earnings are calculated using the 2% of workers with earnings greater than the p-1 and less than the p+1 percentile. A worker is active earch 4 year period if they have at least one quarter of positive earnings in each consecutive 4 year period. Earnings growth shows the percentage increase in average earnings from the first 4 year period to the last 4 year period. Earnings volatility is the variance of the year-to-year change in average annual earnings. Every year a worker is either full year active (earnings in all 4 quarters), partial year active (earnings in at least 1 quarter), and inactive (earnings in 0 quarters). HC fixed person effects and HC average firm effects are estimated using an AKM style earnings regression.

Table 1B: Native-Born Earnings and Activity Measures

Race/Ethnicity	N	Percentile	Average Annual Earnings	Share Active Each 4 Year Period	Earnings Growth (Active Each 4 Year Period)	Earnings Volatility (Arc Pct Change)	Average Annual Hours Worked	Years Partially Active	Years Inactive	HC Fixed Person Effect	HC Average Firm Effect
Native-Born Females											
		10	$2,696	0.24	-0.12	2.31	938	2.60	7.48	-0.03	0.01
		25	$14,390	0.67	-0.09	1.19	1,326	2.33	3.42	-0.05	0.05
Asian Non-Hispanic	321,000	50	$38,350	0.92	0.07	0.44	1,786	1.18	0.94	0.03	0.14
		75	$69,530	0.97	0.17	0.23	1,920	0.72	0.41	0.26	0.25
		90	$108,900	0.98	0.24	0.18	1,952	0.63	0.29	0.51	0.33
		10	$1,208	0.23	-0.23	2.99	673	3.12	8.03	0.01	-0.07
		25	$6,807	0.65	-0.13	1.59	1,009	3.49	3.89	-0.03	-0.05
Black Non-Hispanic	6,311,000	50	$19,320	0.93	-0.09	0.58	1,473	1.73	1.01	0.00	0.01
		75	$35,090	0.97	0.00	0.25	1,861	0.87	0.38	0.08	0.10
		90	$54,370	0.99	0.05	0.17	1,987	0.62	0.23	0.23	0.19
		10	$1,658	0.24	-0.15	2.76	662	2.99	7.82	-0.09	-0.06
		25	$7,922	0.65	-0.03	1.49	1,023	3.16	3.81	-0.13	-0.03
White Hispanic	2,600,000	50	$21,590	0.93	0.00	0.56	1,535	1.64	1.02	-0.10	0.03
		75	$38,970	0.98	0.07	0.23	1,890	0.79	0.35	-0.01	0.11
		90	$59,630	0.99	0.12	0.15	1,999	0.51	0.20	0.16	0.19
		10	$1,727	0.22	-0.14	2.51	607	2.73	7.77	-0.06	-0.07
		25	$8,553	0.63	-0.02	1.32	1,006	2.67	3.80	-0.11	-0.04
White Non-Hispanic	34,340,000	50	$23,790	0.91	-0.02	0.48	1,515	1.33	1.05	-0.06	0.01
		75	$44,180	0.97	0.05	0.22	1,791	0.71	0.41	0.11	0.10
		90	$69,010	0.99	0.10	0.15	1,869	0.51	0.24	0.33	0.17
		10	$843	0.15	-0.29	3.33	582	2.69	8.79	-0.07	-0.07
		25	$4,946	0.51	-0.14	1.97	921	3.58	5.20	-0.12	-0.06
All Other	1,348,000	50	$16,970	0.88	-0.04	0.81	1,374	2.23	1.62	-0.13	-0.01
		75	$34,450	0.97	0.06	0.31	1,817	1.01	0.47	-0.06	0.08
		90	$55,400	0.99	0.13	0.19	1,965	0.66	0.27	0.10	0.17
Native-Born Males											
		10	$3,905	0.29	-0.27	2.42	1,035	2.89	7.21	-0.20	0.01
		25	$19,900	0.76	-0.05	1.05	1,506	2.32	2.69	-0.20	0.03
Asian Non-Hispanic	352,000	50	$49,030	0.94	0.11	0.36	1,949	1.02	0.74	-0.08	0.14
		75	$89,870	0.98	0.18	0.20	2,035	0.64	0.38	0.18	0.29
		90	$146,400	0.98	0.28	0.19	2,018	0.62	0.29	0.49	0.38
		10	$617	0.14	-0.22	3.77	434	2.59	9.13	-0.01	-0.10
		25	$3,927	0.45	-0.16	2.37	820	3.84	6.03	-0.06	-0.06
Black Non-Hispanic	5,757,000	50	$16,780	0.84	-0.09	0.98	1,392	2.66	1.99	-0.07	-0.01
		75	$36,410	0.96	-0.02	0.32	1,906	1.07	0.51	0.02	0.07
		90	$59,180	0.98	0.04	0.19	2,093	0.66	0.28	0.17	0.16
		10	$2,065	0.25	-0.31	2.93	762	3.20	7.87	-0.20	-0.02
		25	$10,550	0.65	-0.17	1.60	1,201	3.49	3.93	-0.22	0.00
White Hispanic	2,556,000	50	$29,160	0.94	-0.01	0.54	1,760	1.68	0.94	-0.19	0.05
		75	$52,060	0.98	0.08	0.22	2,071	0.77	0.33	-0.06	0.13
		90	$80,540	0.99	0.13	0.14	2,156	0.49	0.20	0.13	0.22
		10	$3,469	0.28	-0.32	2.44	887	3.06	7.29	-0.21	-0.01
		25	$16,370	0.71	-0.20	1.15	1,345	2.73	3.07	-0.22	0.00
White Non-Hispanic	35,000,000	50	$38,960	0.94	-0.04	0.36	1,823	1.16	0.73	-0.13	0.05
		75	$67,890	0.98	0.05	0.19	1,988	0.65	0.34	0.09	0.15
		90	$110,400	0.98	0.11	0.16	2,002	0.52	0.27	0.39	0.24
		10	$980	0.16	-0.34	3.51	569	2.78	8.80	-0.21	-0.05
		25	$6,121	0.51	-0.26	2.07	978	3.82	5.31	-0.26	-0.02
All Other	1,284,000	50	$22,140	0.88	-0.08	0.81	1,538	2.37	1.60	-0.25	0.02
		75	$45,210	0.97	0.05	0.29	1,957	1.03	0.48	-0.14	0.10
		90	$73,890	0.99	0.12	0.18	2,074	0.64	0.27	0.05	0.21

Notes: Estimates are created using the 108,800,000 worker sample 2. Average annual earnings show the percentile of worker average earnings at all jobs over the 12 year sample period. All measures except average annual earnings are calculated using the 2% of workers with earnings greater than the p-1 and less than the p+1 percentile. A worker is active earch 4 year period if they have at least one quarter of positive earnings in each consecutive 4 year period. Earnings growth shows the percentage increase in average earnings from the first 4 year period to the last 4 year period. Earnings volatility is the variance of the year-to-year change in average annual earnings. Every year a worker is either full year active (earnings in all 4 quarters), partial year active (earnings in at least 1 quarter), and inactive (earnings in 0 quarters). HC fixed person effects and HC average firm effects are estimated using an AKM style earnings regression.

Table 2A: Foreign-Born Job and Worker Characteristics

Race/Ethnicity	N	Percentile	Division (Top 2) First	Division (Top 2) Second	Division (Top 2) Share	Industry (Top 4) First	Industry (Top 4) Second	Industry (Top 4) Third	Industry (Top 4) Fourth	Industry (Top 4) Share	Age (2004)	Education <HS	Education BA+
Foreign Born Females													
		10	9	2	0.55	R	S	G	P	0.56	39.10	0.24	0.34
		25	9	2	0.58	R	S	G	P	0.58	39.09	0.24	0.33
Asian Non-Hispanic	2,416,000	50	9	2	0.55	P	E	G	R	0.58	39.30	0.19	0.36
		75	9	2	0.61	P	E	O	L	0.56	37.75	0.07	0.59
		90	9	2	0.61	P	L	E	J	0.68	37.31	0.02	0.78
		10	5	2	0.66	P	N	R	G	0.66	38.13	0.25	0.17
		25	5	2	0.70	P	R	G	N	0.68	37.83	0.23	0.17
Black Non-Hispanic	797,000	50	5	2	0.71	P	G	O	R	0.71	38.18	0.18	0.20
		75	2	5	0.72	P	O	J	T	0.72	38.69	0.10	0.32
		90	2	5	0.72	P	O	J	L	0.78	39.09	0.06	0.47
		10	9	5	0.53	N	R	P	G	0.55	39.17	0.58	0.08
		25	9	5	0.53	N	P	R	E	0.52	38.77	0.57	0.08
White Hispanic	3,213,000	50	9	5	0.51	P	E	R	G	0.55	38.61	0.54	0.08
		75	9	5	0.50	P	E	G	R	0.58	38.33	0.44	0.11
		90	9	5	0.55	P	O	E	J	0.54	37.95	0.26	0.22
		10	9	5	0.42	G	P	R	O	0.51	39.14	0.18	0.30
		25	9	5	0.41	P	G	O	R	0.54	38.90	0.15	0.31
White Non-Hispanic	1,935,000	50	9	2	0.38	P	G	O	E	0.56	39.80	0.13	0.31
		75	9	2	0.40	P	O	L	J	0.56	39.60	0.06	0.46
		90	9	2	0.47	P	O	L	J	0.66	39.52	0.03	0.64
		10	9	2	0.48	N	R	P	G	0.56	38.67	0.43	0.16
		25	9	2	0.51	P	N	R	G	0.56	38.15	0.43	0.15
All Other	533,000	50	2	9	0.50	P	E	R	G	0.59	38.03	0.41	0.14
		75	9	2	0.50	P	E	O	R	0.57	37.95	0.28	0.21
		90	9	2	0.57	P	O	J	E	0.57	37.82	0.15	0.38
Foreign Born Males													
		10	9	2	0.57	R	G	S	N	0.50	39.16	0.23	0.36
		25	9	2	0.56	R	G	E	L	0.59	39.00	0.23	0.35
Asian Non-Hispanic	2,423,000	50	9	2	0.54	E	G	R	L	0.54	38.54	0.16	0.40
		75	9	2	0.54	L	E	P	O	0.58	36.87	0.05	0.68
		90	9	2	0.58	L	E	J	I	0.66	36.73	0.02	0.85
		10	5	2	0.62	N	G	R	D	0.52	38.69	0.24	0.20
		25	5	2	0.65	N	G	P	R	0.48	38.14	0.24	0.20
Black Non-Hispanic	794,000	50	5	2	0.67	P	G	E	N	0.47	38.31	0.22	0.20
		75	2	5	0.66	P	E	H	O	0.46	38.67	0.14	0.29
		90	2	5	0.67	O	P	H	E	0.50	39.51	0.09	0.42
		10	9	5	0.50	D	N	R	E	0.58	38.94	0.60	0.07
		25	9	5	0.53	D	N	E	R	0.57	38.96	0.61	0.07
White Hispanic	3,976,000	50	9	5	0.51	E	D	N	R	0.56	38.99	0.60	0.07
		75	9	5	0.50	E	D	G	F	0.55	38.06	0.52	0.09
		90	9	7	0.52	E	D	F	H	0.52	37.98	0.42	0.14
		10	9	5	0.42	R	D	G	N	0.50	39.26	0.21	0.29
		25	9	2	0.43	G	D	R	E	0.47	38.87	0.18	0.31
White Non-Hispanic	2,188,000	50	2	5	0.37	E	G	D	R	0.46	39.50	0.13	0.34
		75	2	9	0.42	E	L	O	D	0.49	39.69	0.06	0.52
		90	9	2	0.47	L	E	F	J	0.57	39.72	0.03	0.73
		10	9	2	0.46	N	D	R	G	0.55	38.83	0.45	0.15
		25	9	2	0.48	N	D	E	G	0.53	38.32	0.46	0.13
All Other	610,000	50	9	2	0.48	E	D	N	R	0.52	38.35	0.46	0.13
		75	9	2	0.49	E	D	G	R	0.48	37.81	0.38	0.18
		90	9	2	0.56	E	D	O	H	0.42	37.87	0.24	0.31

Notes: Estimates are created using the 108,800,000 worker sample 2. All measures are calculated using the 2% of workers with earnings greater than the p-1 and less than the p+1 percentile. Please see Appendix Table A2 for definitions of the division and industry codes. The Share shows the percent of workers in the top 2 divisions or the top 4 industries.

Table 2B: Native-Born Job and Worker Characteristics

			Division (Top 2)			Industry (Top 4)						Education	
Race/Ethnicity	N	Percentile	First	Second	Share	First	Second	Third	Fourth	Share	Age (2004)	<HS	BA+
Native-Born Females													
		10	9	5	0.65	P	G	O	R	0.52	36.77	0.13	0.33
		25	9	5	0.65	P	O	G	L	0.54	36.30	0.10	0.35
Asian Non-Hispanic	321,000	50	9	2	0.70	P	O	L	J	0.55	35.91	0.05	0.43
		75	9	2	0.74	P	O	L	J	0.62	35.87	0.02	0.62
		90	9	2	0.74	P	L	J	E	0.60	35.24	0.02	0.74
		10	5	3	0.49	P	N	R	G	0.65	38.73	0.26	0.10
		25	5	3	0.50	P	R	N	G	0.64	37.98	0.22	0.10
Black Non-Hispanic	6,311,000	50	5	7	0.52	P	O	G	E	0.63	38.34	0.15	0.12
		75	5	3	0.50	P	O	T	J	0.62	38.57	0.08	0.20
		90	5	2	0.49	O	P	T	J	0.64	39.00	0.04	0.37
		10	7	9	0.56	P	G	R	N	0.58	36.70	0.26	0.12
		25	7	9	0.56	P	G	O	R	0.59	36.22	0.23	0.12
White Hispanic	2,600,000	50	7	9	0.56	P	O	G	J	0.58	36.43	0.16	0.14
		75	9	7	0.56	P	O	T	J	0.59	36.32	0.09	0.23
		90	9	7	0.58	O	P	T	J	0.61	36.94	0.04	0.38
		10	5	3	0.37	G	P	O	R	0.57	39.38	0.12	0.22
		25	3	5	0.38	P	G	O	R	0.59	39.24	0.10	0.21
White Non-Hispanic	34,340,000	50	3	5	0.38	P	O	G	E	0.59	39.97	0.06	0.23
		75	5	3	0.36	O	P	J	E	0.61	39.79	0.02	0.40
		90	3	2	0.34	P	O	J	L	0.67	40.39	0.01	0.58
		10	9	8	0.42	P	G	R	N	0.57	37.66	0.23	0.13
		25	9	8	0.42	P	G	R	N	0.57	36.78	0.20	0.13
All Other	1,348,000	50	9	8	0.42	P	G	O	R	0.55	36.78	0.14	0.15
		75	9	7	0.44	P	O	T	J	0.56	36.86	0.08	0.22
		90	9	2	0.49	O	P	T	J	0.59	37.34	0.04	0.38
Native-Born Males													
		10	9	5	0.66	G	N	R	D	0.44	36.15	0.15	0.28
		25	9	5	0.65	G	R	L	P	0.41	35.52	0.11	0.29
Asian Non-Hispanic	352,000	50	9	2	0.70	G	L	E	O	0.39	35.88	0.06	0.38
		75	9	2	0.74	L	E	T	P	0.50	36.15	0.02	0.61
		90	9	2	0.73	L	E	P	J	0.63	36.52	0.01	0.76
		10	5	3	0.48	N	R	D	G	0.59	37.98	0.28	0.09
		25	5	3	0.48	N	R	E	D	0.55	37.55	0.26	0.09
Black Non-Hispanic	5,757,000	50	5	7	0.50	E	N	G	H	0.48	37.92	0.21	0.09
		75	5	7	0.51	E	T	H	P	0.48	38.55	0.14	0.13
		90	5	7	0.47	E	T	H	O	0.54	39.20	0.08	0.22
		10	9	7	0.53	D	N	G	R	0.54	36.42	0.29	0.11
		25	9	7	0.54	D	G	E	N	0.51	35.76	0.25	0.11
White Hispanic	2,556,000	50	7	9	0.55	E	G	D	F	0.46	35.91	0.20	0.12
		75	9	7	0.58	E	D	T	O	0.45	36.33	0.13	0.19
		90	9	7	0.58	T	E	D	O	0.45	37.05	0.07	0.32
		10	5	3	0.36	D	G	N	E	0.52	39.30	0.17	0.18
		25	5	3	0.38	D	E	G	N	0.50	39.12	0.14	0.18
White Non-Hispanic	35,000,000	50	3	5	0.38	E	D	G	F	0.50	39.21	0.09	0.21
		75	3	5	0.36	E	D	O	L	0.47	39.62	0.04	0.36
		90	3	2	0.33	E	L	F	J	0.51	40.39	0.02	0.60
		10	9	8	0.42	N	D	R	G	0.55	37.63	0.25	0.11
		25	9	8	0.43	D	N	G	E	0.50	36.64	0.22	0.11
All Other	1,284,000	50	9	8	0.42	E	D	G	T	0.45	36.57	0.16	0.13
		75	9	7	0.47	E	D	T	G	0.45	37.05	0.10	0.20
		90	9	7	0.51	E	T	D	L	0.45	37.61	0.05	0.33

Notes: Estimates are created using the 108,800,000 worker sample 2. All measures are calculated using the 2% of workers with earnings greater than the p-1 and less than the p+1 percentile. Please see Appendix Table A2 for definitions of the division and industry codes. The Share shows the percent of workers in the top 2 divisions or the top 4 industries.

Table 3: Average Annual Earnings OLS Regression Estimates

Parameter	Model 1	Model 2	Model 3	Model 4	Model 5
Intercept	10.17	6.683	6.52	6.465	6.836
Foreign-Born Females					
Asian Non Hispanic	-0.64	-0.18	-0.20	-0.23	-0.30
Black Non-Hispanic	-0.43	-0.40	-0.44	-0.41	-0.49
White Hispanic	-1.21	-0.42	-0.39	-0.33	-0.40
White Non-Hispanic	-0.84	-0.10	-0.15	-0.16	-0.28
All Other	-1.08	-0.43	-0.43	-0.38	-0.39
Foreign-Born Males					
Asian Non Hispanic	-0.23	-0.08	-0.10	-0.13	-0.20
Black Non-Hispanic	-0.53	-0.39	-0.39	-0.37	-0.38
White Hispanic	-0.71	-0.46	-0.41	-0.35	-0.31
White Non-Hispanic	-0.35	0.03	0.01	-0.02	-0.18
All Other	-0.78	-0.43	-0.40	-0.36	-0.27
Native-Born Females					
Asian Non Hispanic	-0.08	0.04	-0.05	-0.05	-0.18
Black Non-Hispanic	-0.80	-0.32	-0.33	-0.29	-0.41
White Hispanic	-0.64	-0.27	-0.30	-0.25	-0.26
White Non-Hispanic	-0.54	-0.05	-0.09	-0.09	-0.14
All Other	-0.94	-0.26	-0.27	-0.23	-0.22
Native-Born Males					
Asian Non Hispanic	0.22	0.08	0.03	0.02	-0.01
Black Non-Hispanic	-1.02	-0.32	-0.28	-0.24	-0.32
White Hispanic	-0.36	-0.27	-0.27	-0.22	-0.15
White Non-Hispanic	0.00	0.00	0.00	0.00	0.00
All Other	-0.70	-0.22	-0.21	-0.17	-0.07
Covariates					
Hours	No	Yes	Yes	Yes	Yes
Division/Industry	No	No	Yes	Yes	Yes
Age and Education	No	No	No	Yes	No
Age, HC Fixed Person, and Firm Effects	No	No	No	No	Yes
Summary Statistics					
R2	0.04	0.87	0.89	0.89	0.93
Observations	108,800,000	108,800,000	108,800,000	108,800,000	108,800,000

Notes: Estimates are created using the 108,800,000 worker sample 2. The hours covariates include a quartic in hours worked, paritial years worked, and inactive years worked. The region/industry covariates include indicator variables for 9 Census Divisions and 21 NAICS 2017 industry sectors. Please see Appendix Table A2 for definitions of the division and industry codes. The age and education covariates include age in 2004 and education indicator variables for less than HS, HS grad, some college, and BA+. The Age, HC Fixed Person and HC Average Firm effects include age in 2004 and the fixed effects from an AKM style earnings regression. Due to the large sample size, standard errors are not reported.

Table 4A - Foreign-Born Earnings Simulation

Race/Ethnicity	Percentile θ	Q(θ)|g - Q(θ)|0	Predicted Log Earnings at Quantile Q(θ): Q(θ)|β(g),x(g)	Q(θ)|β(0),x(0)	Q(θ)|β(0),x(g)	Q(θ)|β(g),x(0)	Predicted Diff Log Earn	Residual Diff Log Earn
Foreign-Born Females								
Asian Non-Hispanic	10	-1.18	6.77	7.91	6.94	7.75	-1.14	-0.04
	25	-0.96	8.62	9.71	8.78	9.53	-1.09	0.13
	50	-0.58	10.11	10.64	10.32	10.41	-0.53	-0.05
	75	-0.32	10.77	11.08	11.05	10.82	-0.31	-0.01
	90	-0.22	11.26	11.56	11.67	11.23	-0.30	0.08
Black Non-Hispanic	10	-0.29	7.63	7.91	7.77	7.75	-0.28	-0.02
	25	-0.40	9.25	9.71	9.48	9.43	-0.46	0.06
	50	-0.45	10.20	10.64	10.53	10.28	-0.44	-0.01
	75	-0.46	10.64	11.08	11.14	10.61	-0.44	-0.02
	90	-0.48	11.03	11.56	11.77	10.96	-0.53	0.05
White Hispanic	10	-1.68	6.37	7.91	6.48	7.72	-1.54	-0.14
	25	-1.44	8.06	9.71	8.22	9.41	-1.65	0.21
	50	-1.11	9.49	10.64	9.73	10.22	-1.16	0.05
	75	-0.99	10.20	11.08	10.60	10.54	-0.88	-0.11
	90	-0.98	10.59	11.56	11.16	10.83	-0.97	-0.01
White Non-Hispanic	10	-1.63	6.35	7.91	6.56	7.80	-1.56	-0.07
	25	-1.20	8.34	9.71	8.43	9.63	-1.37	0.17
	50	-0.70	9.96	10.64	10.06	10.47	-0.68	-0.02
	75	-0.47	10.66	11.08	10.85	10.88	-0.42	-0.05
	90	-0.40	11.12	11.56	11.43	11.32	-0.44	0.04
All Other	10	-1.65	6.38	7.91	6.55	7.69	-1.53	-0.12
	25	-1.33	8.18	9.71	8.40	9.39	-1.53	0.20
	50	-0.97	9.66	10.64	9.97	10.22	-0.98	0.02
	75	-0.82	10.36	11.08	10.81	10.56	-0.72	-0.10
	90	-0.78	10.76	11.56	11.39	10.90	-0.80	0.02
Foreign-Born Males								
Asian Non-Hispanic	10	-0.75	7.17	7.91	7.33	7.78	-0.74	0.00
	25	-0.50	9.17	9.71	9.32	9.60	-0.54	0.04
	50	-0.17	10.50	10.64	10.66	10.50	-0.14	-0.03
	75	0.10	11.14	11.08	11.26	10.97	0.06	0.04
	90	0.13	11.69	11.56	11.85	11.45	0.13	0.00
Black Non-Hispanic	10	-0.83	7.07	7.91	7.25	7.75	-0.84	0.00
	25	-0.63	9.00	9.71	9.24	9.49	-0.72	0.08
	50	-0.43	10.22	10.64	10.53	10.34	-0.42	-0.01
	75	-0.39	10.71	11.08	11.14	10.69	-0.37	-0.02
	90	-0.41	11.12	11.56	11.72	11.06	-0.44	0.03
White Hispanic	10	-1.06	6.87	7.91	6.99	7.75	-1.05	-0.02
	25	-0.80	8.77	9.71	9.01	9.45	-0.94	0.14
	50	-0.60	10.04	10.64	10.37	10.32	-0.60	0.00
	75	-0.58	10.56	11.08	10.97	10.64	-0.52	-0.06
	90	-0.65	10.91	11.56	11.45	11.00	-0.65	0.00
White Non-Hispanic	10	-1.30	6.61	7.91	6.80	7.81	-1.30	0.00
	25	-0.71	8.91	9.71	8.97	9.70	-0.80	0.09
	50	-0.19	10.48	10.64	10.52	10.59	-0.16	-0.03
	75	0.06	11.13	11.08	11.14	11.09	0.05	0.01
	90	0.18	11.74	11.56	11.69	11.63	0.18	0.00
All Other	10	-1.36	6.60	7.91	6.78	7.73	-1.31	-0.05
	25	-0.98	8.58	9.71	8.83	9.46	-1.14	0.15
	50	-0.63	10.01	10.64	10.34	10.32	-0.63	0.00
	75	-0.54	10.61	11.08	11.02	10.68	-0.47	-0.07
	90	-0.53	11.02	11.56	11.55	11.08	-0.54	0.01

Notes: Estimates are created using the 108,800,000 worker sample 2. All measures are calculated using the 2% of workers with earnings greater than the p-1 and less than the p+1 percentile. See section IV.c.i. of the paper for more details.

Table 4B - Native-Born Earnings Simulation

Race/Ethnicity	Percentile θ	Q(θ)|g - Q(θ)|0	Predicted Log Earnings at Quantile Q(θ): Q(θ)|β(g),x(g)	Q(θ)|β(0),x(0)	Q(θ)|β(0),x(g)	Q(θ)|β(g),x(0)	Predicted Diff Log Earn	Residual Diff Log Earn
Native-Born Females								
Asian Non-Hispanic	10	-0.25	7.67	7.91	7.75	7.82	-0.24	-0.01
	25	-0.13	9.60	9.71	9.63	9.69	-0.11	-0.02
	50	-0.02	10.60	10.64	10.63	10.60	-0.04	0.02
	75	0.02	11.08	11.08	11.14	11.07	0.00	0.02
	90	-0.01	11.56	11.56	11.70	11.55	0.00	-0.01
Black Non-Hispanic	10	-1.05	6.89	7.91	6.94	7.79	-1.02	-0.04
	25	-0.88	8.69	9.71	8.80	9.49	-1.02	0.14
	50	-0.70	9.94	10.64	10.15	10.34	-0.70	0.00
	75	-0.66	10.49	11.08	10.82	10.67	-0.59	-0.07
	90	-0.71	10.83	11.56	11.36	11.00	-0.73	0.02
White Hispanic	10	-0.74	7.19	7.91	7.23	7.80	-0.72	-0.02
	25	-0.73	8.87	9.71	8.99	9.50	-0.84	0.12
	50	-0.59	10.06	10.64	10.26	10.37	-0.58	-0.01
	75	-0.56	10.57	11.08	10.87	10.72	-0.51	-0.05
	90	-0.62	10.91	11.56	11.39	11.06	-0.65	0.03
White Non-Hispanic	10	-0.70	7.22	7.91	7.22	7.88	-0.69	0.00
	25	-0.65	8.96	9.71	8.96	9.64	-0.75	0.10
	50	-0.49	10.17	10.64	10.21	10.52	-0.47	-0.02
	75	-0.43	10.68	11.08	10.80	10.91	-0.40	-0.03
	90	-0.47	11.05	11.56	11.33	11.29	-0.51	0.04
All Other	10	-1.41	6.59	7.91	6.64	7.80	-1.32	-0.09
	25	-1.20	8.33	9.71	8.41	9.52	-1.38	0.19
	50	-0.83	9.80	10.64	9.95	10.37	-0.84	0.01
	75	-0.68	10.48	11.08	10.74	10.74	-0.60	-0.08
	90	-0.69	10.86	11.56	11.29	11.08	-0.70	0.01
Native-Born Males								
Asian Non-Hispanic	10	0.12	8.06	7.91	8.11	7.90	0.15	-0.03
	25	0.20	9.97	9.71	9.96	9.74	0.26	-0.06
	50	0.23	10.82	10.64	10.80	10.68	0.18	0.05
	75	0.28	11.35	11.08	11.30	11.19	0.27	0.01
	90	0.28	11.89	11.56	11.84	11.69	0.33	-0.05
Black Non-Hispanic	10	-1.73	6.30	7.91	6.37	7.82	-1.61	-0.12
	25	-1.43	8.07	9.71	8.14	9.55	-1.65	0.22
	50	-0.84	9.78	10.64	9.93	10.40	-0.86	0.02
	75	-0.62	10.53	11.08	10.79	10.75	-0.55	-0.07
	90	-0.62	10.92	11.56	11.29	11.09	-0.64	0.02
White Hispanic	10	-0.52	7.38	7.91	7.43	7.85	-0.53	0.01
	25	-0.44	9.21	9.71	9.35	9.57	-0.51	0.07
	50	-0.29	10.37	10.64	10.56	10.46	-0.27	-0.02
	75	-0.27	10.83	11.08	11.07	10.84	-0.25	-0.02
	90	-0.32	11.22	11.56	11.54	11.23	-0.34	0.02
White Non-Hispanic	10	0.00	7.91	7.91	7.91	7.91	0.00	0.00
	25	0.00	9.71	9.71	9.71	9.71	0.00	0.00
	50	0.00	10.64	10.64	10.64	10.64	0.00	0.00
	75	0.00	11.08	11.08	11.08	11.08	0.00	0.00
	90	0.00	11.56	11.56	11.56	11.56	0.00	0.00
All Other	10	-1.26	6.69	7.91	6.73	7.85	-1.22	-0.05
	25	-0.98	8.57	9.71	8.64	9.61	-1.14	0.16
	50	-0.57	10.09	10.64	10.22	10.48	-0.55	-0.02
	75	-0.41	10.72	11.08	10.91	10.87	-0.36	-0.05
	90	-0.40	11.14	11.56	11.40	11.26	-0.42	0.02

Notes: Estimates are created using the 108,800,000 worker sample 2. All measures are calculated using the 2% of workers with earnings greater than the p-1 and less than the p+1 percentile. See section IV.c.i. of the paper for more details.

Table 5A - Foreign-Born Earnings Decompositions

			Decomposition 1: Q(θ)|β(g),x(g) - Q(θ)|β(g),x(0) + Q(θ)|β(g),x(0) - Q(θ)|β(0),x(0)				Decomposition 2: Q(θ)|β(0),x(g) - Q(θ)|β(0),x(0) + Q(θ)|β(g),x(g) - Q(θ)|β(0),x(g)			
			Components		Share of Difference		Components		Share of Difference	
Race/Ethnicity	Percentile θ	Predicted Diff Log Earn	Covariates	Coefficients	Covariates	Coefficients	Covariates	Coefficients	Covariates	Coefficients
Foreign-Born Females										
	10	-1.14	-0.98	-0.16	0.86	0.14	-0.97	-0.18	0.85	0.15
	25	-1.09	-0.91	-0.19	0.83	0.17	-0.93	-0.16	0.85	0.15
Asian Non-Hispanic	50	-0.53	-0.30	-0.23	0.57	0.43	-0.32	-0.21	0.60	0.40
	75	-0.31	-0.05	-0.26	0.16	0.84	-0.03	-0.28	0.10	0.90
	90	-0.30	0.03	-0.33	-0.10	1.10	0.11	-0.41	-0.37	1.37
	10	-0.28	-0.11	-0.16	0.41	0.59	-0.14	-0.13	0.52	0.48
	25	-0.46	-0.18	-0.29	0.38	0.62	-0.23	-0.23	0.50	0.50
Black Non-Hispanic	50	-0.44	-0.08	-0.36	0.18	0.82	-0.11	-0.33	0.25	0.75
	75	-0.44	0.03	-0.47	-0.07	1.07	0.06	-0.50	-0.14	1.14
	90	-0.53	0.07	-0.60	-0.13	1.13	0.21	-0.74	-0.40	1.40
	10	-1.54	-1.35	-0.19	0.88	0.12	-1.43	-0.10	0.93	0.07
	25	-1.65	-1.35	-0.31	0.81	0.19	-1.49	-0.16	0.90	0.10
White Hispanic	50	-1.16	-0.74	-0.42	0.64	0.36	-0.91	-0.25	0.79	0.21
	75	-0.88	-0.34	-0.54	0.39	0.61	-0.48	-0.40	0.55	0.45
	90	-0.97	-0.24	-0.73	0.25	0.75	-0.40	-0.57	0.41	0.59
	10	-1.56	-1.45	-0.11	0.93	0.07	-1.35	-0.21	0.86	0.14
	25	-1.37	-1.29	-0.09	0.94	0.06	-1.28	-0.09	0.93	0.07
White Non-Hispanic	50	-0.68	-0.51	-0.17	0.75	0.25	-0.58	-0.10	0.85	0.15
	75	-0.42	-0.22	-0.20	0.52	0.48	-0.23	-0.19	0.55	0.45
	90	-0.44	-0.20	-0.24	0.45	0.55	-0.13	-0.31	0.30	0.70
	10	-1.53	-1.31	-0.22	0.86	0.14	-1.36	-0.18	0.88	0.12
	25	-1.53	-1.21	-0.32	0.79	0.21	-1.31	-0.22	0.85	0.15
All Other	50	-0.98	-0.56	-0.42	0.57	0.43	-0.68	-0.31	0.69	0.31
	75	-0.72	-0.20	-0.52	0.28	0.72	-0.27	-0.45	0.37	0.63
	90	-0.80	-0.14	-0.66	0.18	0.82	-0.17	-0.63	0.21	0.79
Foreign-Born Males										
	10	-0.74	-0.62	-0.13	0.83	0.17	-0.58	-0.17	0.78	0.22
	25	-0.54	-0.42	-0.12	0.78	0.22	-0.39	-0.15	0.72	0.28
Asian Non-Hispanic	50	-0.14	0.00	-0.14	0.00	1.00	0.02	-0.16	-0.14	1.14
	75	0.06	0.17	-0.11	2.83	-1.83	0.18	-0.12	3.00	-2.00
	90	0.13	0.24	-0.11	1.85	-0.85	0.29	-0.16	2.23	-1.23
	10	-0.84	-0.68	-0.16	0.81	0.19	-0.66	-0.18	0.79	0.21
	25	-0.72	-0.49	-0.23	0.68	0.32	-0.47	-0.24	0.66	0.34
Black Non-Hispanic	50	-0.42	-0.12	-0.30	0.29	0.71	-0.11	-0.31	0.26	0.74
	75	-0.37	0.02	-0.39	-0.05	1.05	0.06	-0.43	-0.16	1.16
	90	-0.44	0.06	-0.50	-0.14	1.14	0.16	-0.60	-0.36	1.36
	10	-1.05	-0.88	-0.16	0.85	0.15	-0.92	-0.12	0.88	0.12
	25	-0.94	-0.68	-0.26	0.72	0.28	-0.70	-0.24	0.75	0.25
White Hispanic	50	-0.60	-0.28	-0.32	0.47	0.53	-0.27	-0.33	0.45	0.55
	75	-0.52	-0.08	-0.44	0.15	0.85	-0.11	-0.41	0.21	0.79
	90	-0.65	-0.09	-0.56	0.14	0.86	-0.11	-0.54	0.17	0.83
	10	-1.30	-1.20	-0.09	0.93	0.07	-1.11	-0.19	0.85	0.15
	25	-0.80	-0.79	-0.01	0.98	0.02	-0.75	-0.05	0.93	0.07
White Non-Hispanic	50	-0.16	-0.11	-0.05	0.69	0.31	-0.12	-0.04	0.75	0.25
	75	0.05	0.04	0.01	0.80	0.20	0.06	-0.01	1.20	-0.20
	90	0.18	0.11	0.07	0.61	0.39	0.13	0.05	0.72	0.28
	10	-1.31	-1.13	-0.18	0.86	0.14	-1.13	-0.18	0.86	0.14
	25	-1.14	-0.88	-0.25	0.78	0.22	-0.88	-0.26	0.78	0.22
All Other	50	-0.63	-0.31	-0.32	0.49	0.51	-0.30	-0.33	0.48	0.52
	75	-0.47	-0.07	-0.40	0.15	0.85	-0.06	-0.41	0.13	0.87
	90	-0.54	-0.06	-0.48	0.11	0.89	-0.01	-0.53	0.02	0.98

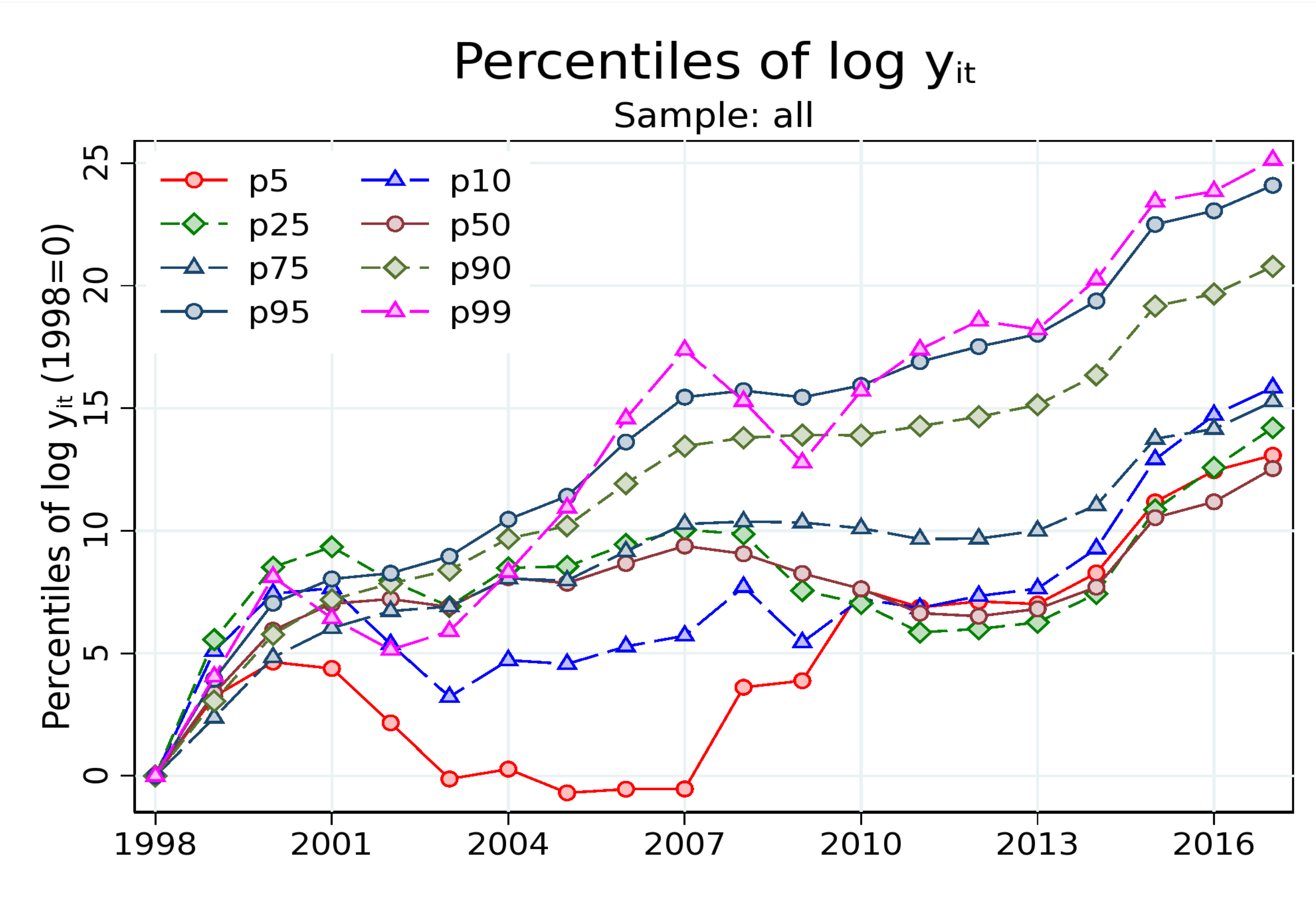
Notes: Estimates are created using the 108,800,000 worker sample 2. All measures are calculated using the 2% of workers with earnings greater than the p-1 and less than the p+1 percentile. See section IV.c.i. of the paper for more details.

Table 5B - Native-Born Earnings Decompositions

Race/Ethnicity	Percentile θ	Predicted Diff Log Earn	Decomposition 1: Q(θ)|β(g),x(g) - Q(θ)|β(g),x(0) + Q(θ)|β(g),x(0) - Q(θ)|β(0),x(0) — Components: Covariates	Components: Coefficients	Share of Difference: Covariates	Share of Difference: Coefficients	Decomposition 2: Q(θ)|β(0),x(g) - Q(θ)|β(0),x(0) + Q(θ)|β(g),x(g) - Q(θ)|β(0),x(g) — Components: Covariates	Components: Coefficients	Share of Difference: Covariates	Share of Difference: Coefficients
Native-Born Females										
Asian Non-Hispanic	10	-0.24	-0.16	-0.09	0.65	0.35	-0.16	-0.09	0.64	0.36
	25	-0.11	-0.08	-0.03	0.75	0.25	-0.08	-0.03	0.75	0.25
	50	-0.04	0.00	-0.04	0.00	1.00	-0.01	-0.03	0.25	0.75
	75	0.00	0.01	-0.01			0.06	-0.06		
	90	0.00	0.01	-0.01			0.14	-0.14		
Black Non-Hispanic	10	-1.02	-0.89	-0.12	0.88	0.12	-0.97	-0.05	0.95	0.05
	25	-1.02	-0.80	-0.22	0.78	0.22	-0.91	-0.11	0.89	0.11
	50	-0.70	-0.40	-0.30	0.57	0.43	-0.49	-0.21	0.70	0.30
	75	-0.59	-0.18	-0.41	0.31	0.69	-0.26	-0.33	0.44	0.56
	90	-0.73	-0.17	-0.56	0.23	0.77	-0.20	-0.53	0.27	0.73
White Hispanic	10	-0.72	-0.60	-0.11	0.84	0.16	-0.68	-0.04	0.94	0.06
	25	-0.84	-0.63	-0.22	0.74	0.26	-0.72	-0.12	0.85	0.15
	50	-0.58	-0.31	-0.27	0.53	0.47	-0.38	-0.20	0.66	0.34
	75	-0.51	-0.15	-0.36	0.29	0.71	-0.21	-0.30	0.41	0.59
	90	-0.65	-0.15	-0.50	0.23	0.77	-0.17	-0.48	0.26	0.74
White Non-Hispanic	10	-0.69	-0.67	-0.03	0.96	0.04	-0.70	0.00	1.00	0.00
	25	-0.75	-0.68	-0.07	0.90	0.10	-0.76	0.01	1.01	-0.01
	50	-0.47	-0.35	-0.12	0.74	0.26	-0.43	-0.04	0.91	0.09
	75	-0.40	-0.23	-0.17	0.58	0.42	-0.28	-0.12	0.70	0.30
	90	-0.51	-0.24	-0.27	0.47	0.53	-0.23	-0.28	0.45	0.55
All Other	10	-1.32	-1.21	-0.11	0.91	0.09	-1.27	-0.05	0.96	0.04
	25	-1.38	-1.19	-0.19	0.86	0.14	-1.30	-0.08	0.94	0.06
	50	-0.84	-0.57	-0.27	0.68	0.32	-0.69	-0.15	0.82	0.18
	75	-0.60	-0.26	-0.34	0.43	0.57	-0.34	-0.26	0.57	0.43
	90	-0.70	-0.22	-0.48	0.31	0.69	-0.27	-0.43	0.39	0.61
Native-Born Males										
Asian Non-Hispanic	10	0.15	0.16	-0.01	1.08	-0.08	0.20	-0.05	1.32	-0.32
	25	0.26	0.23	0.03	0.89	0.11	0.25	0.00	0.98	0.02
	50	0.18	0.14	0.04	0.78	0.22	0.16	0.02	0.89	0.11
	75	0.27	0.16	0.11	0.59	0.41	0.22	0.05	0.81	0.19
	90	0.33	0.20	0.13	0.61	0.39	0.28	0.05	0.85	0.15
Black Non-Hispanic	10	-1.61	-1.52	-0.09	0.94	0.06	-1.54	-0.07	0.96	0.04
	25	-1.65	-1.49	-0.16	0.90	0.10	-1.57	-0.07	0.96	0.04
	50	-0.86	-0.62	-0.24	0.72	0.28	-0.71	-0.15	0.82	0.18
	75	-0.55	-0.22	-0.33	0.40	0.60	-0.29	-0.26	0.53	0.47
	90	-0.64	-0.17	-0.47	0.27	0.73	-0.27	-0.37	0.42	0.58
White Hispanic	10	-0.53	-0.47	-0.06	0.88	0.12	-0.48	-0.05	0.91	0.09
	25	-0.51	-0.36	-0.14	0.72	0.28	-0.36	-0.14	0.72	0.28
	50	-0.27	-0.09	-0.18	0.33	0.67	-0.08	-0.19	0.30	0.70
	75	-0.25	-0.01	-0.24	0.04	0.96	-0.01	-0.24	0.04	0.96
	90	-0.34	-0.01	-0.33	0.03	0.97	-0.02	-0.32	0.06	0.94
White Non-Hispanic	10	0.00	0.00	0.00			0.00	0.00		
	25	0.00	0.00	0.00			0.00	0.00		
	50	0.00	0.00	0.00			0.00	0.00		
	75	0.00	0.00	0.00			0.00	0.00		
	90	0.00	0.00	0.00			0.00	0.00		
All Other	10	-1.22	-1.16	-0.06	0.95	0.05	-1.18	-0.03	0.97	0.03
	25	-1.14	-1.04	-0.10	0.91	0.09	-1.07	-0.07	0.94	0.06
	50	-0.55	-0.39	-0.16	0.71	0.29	-0.42	-0.13	0.76	0.24
	75	-0.36	-0.15	-0.21	0.42	0.58	-0.17	-0.19	0.47	0.53
	90	-0.42	-0.12	-0.30	0.29	0.71	-0.16	-0.26	0.38	0.62

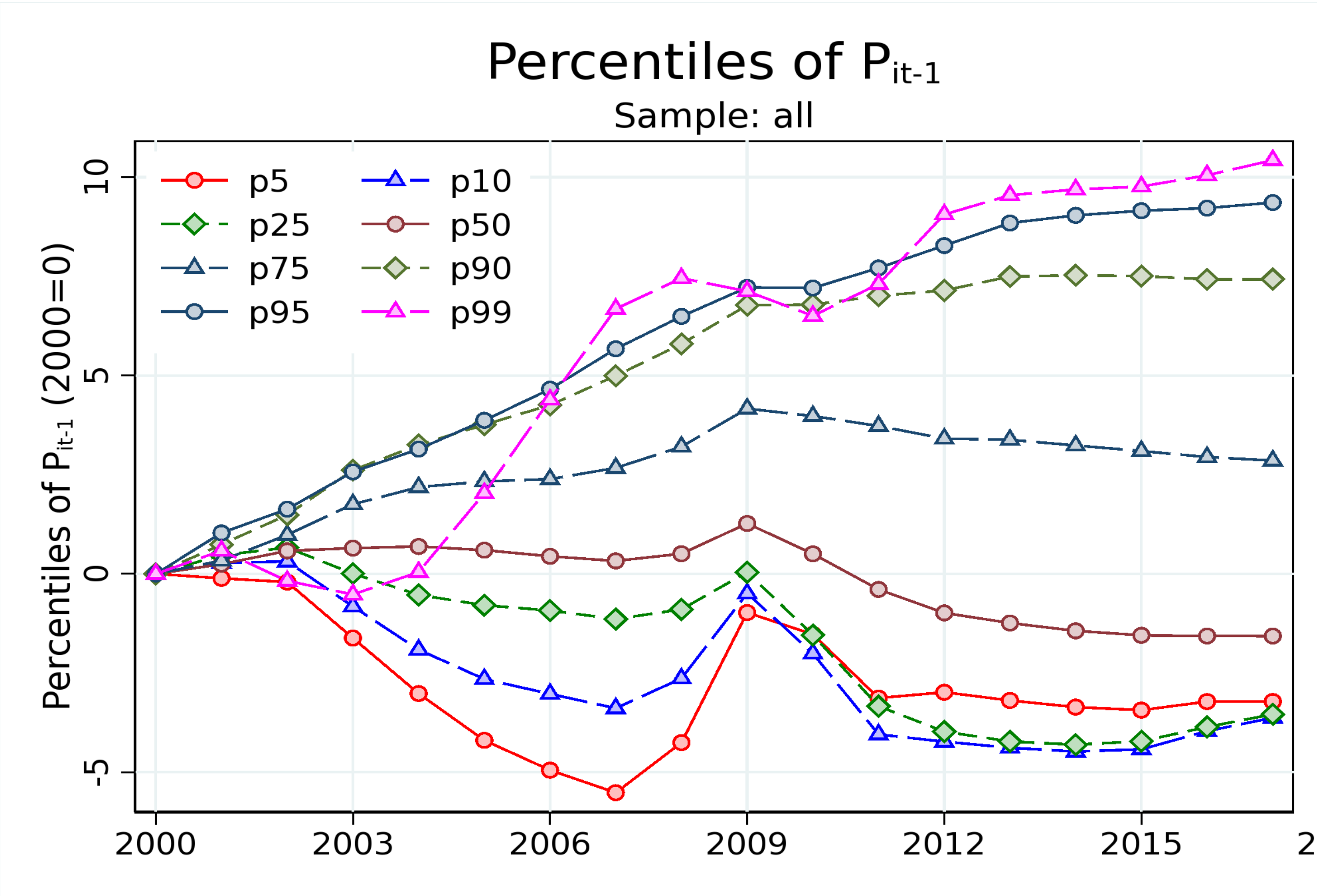
Notes: Estimates are created using the 108,800,000 worker sample 2. All measures are calculated using the 2% of workers with earnings greater than the p-1 and less than the p+1 percentile. See section IV.c.i. of the paper for more details.

Figure 1: Percentage Change in the Percentiles of Log Real Annual Earnings by Year



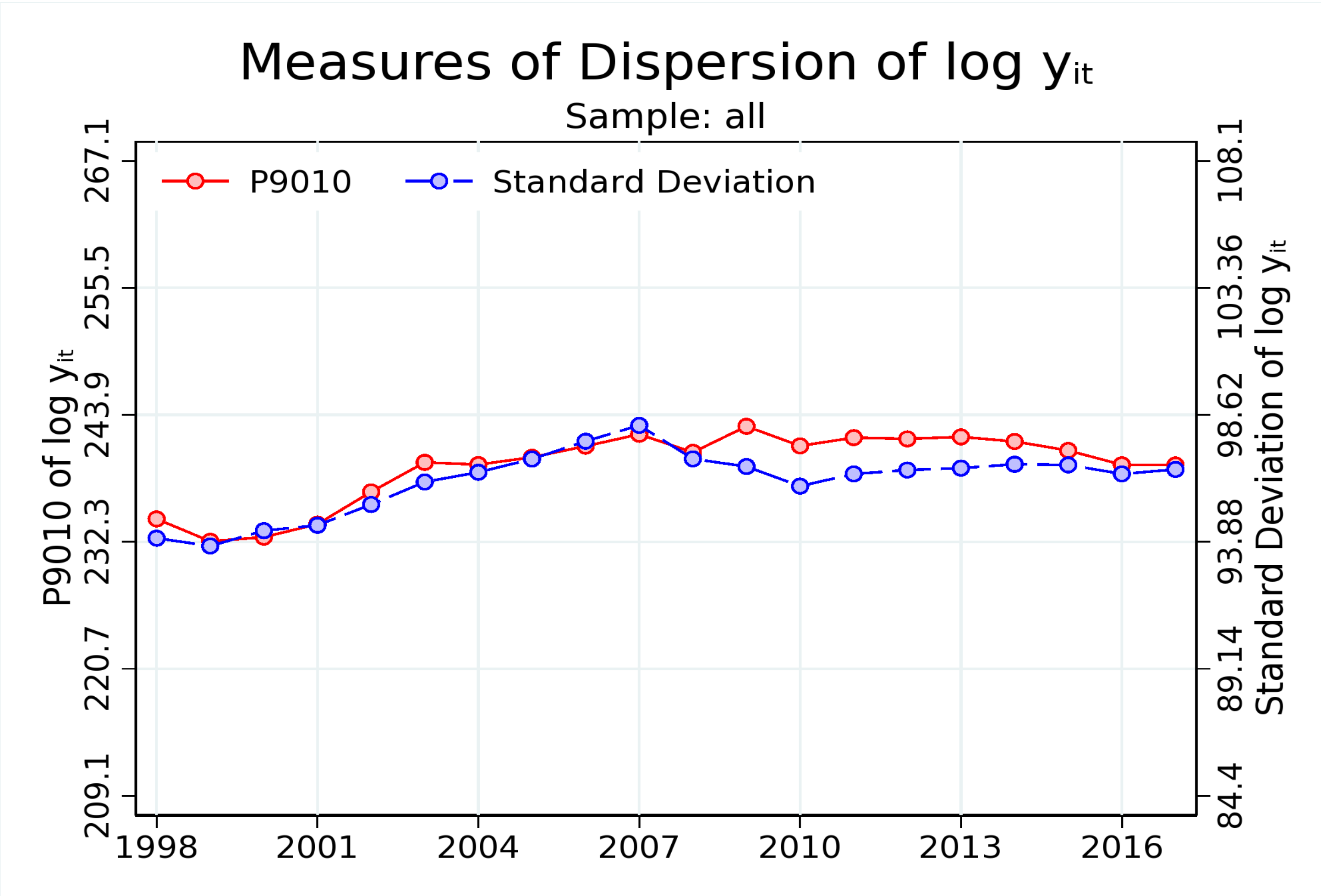
Notes: Calculations are based on the 1.8 billion person-year records in sample 1. Y is real (2018 PCE) log annual earnings at all jobs. Only person-year records above 260* federal minimum wage in that year are included. The y-axis shows the difference in log real earnings between the current year and the base year (1998) multiplied by 100.

Figure 2: Percentage Change in the Percentiles of Log Real Permanent Earnings by Year



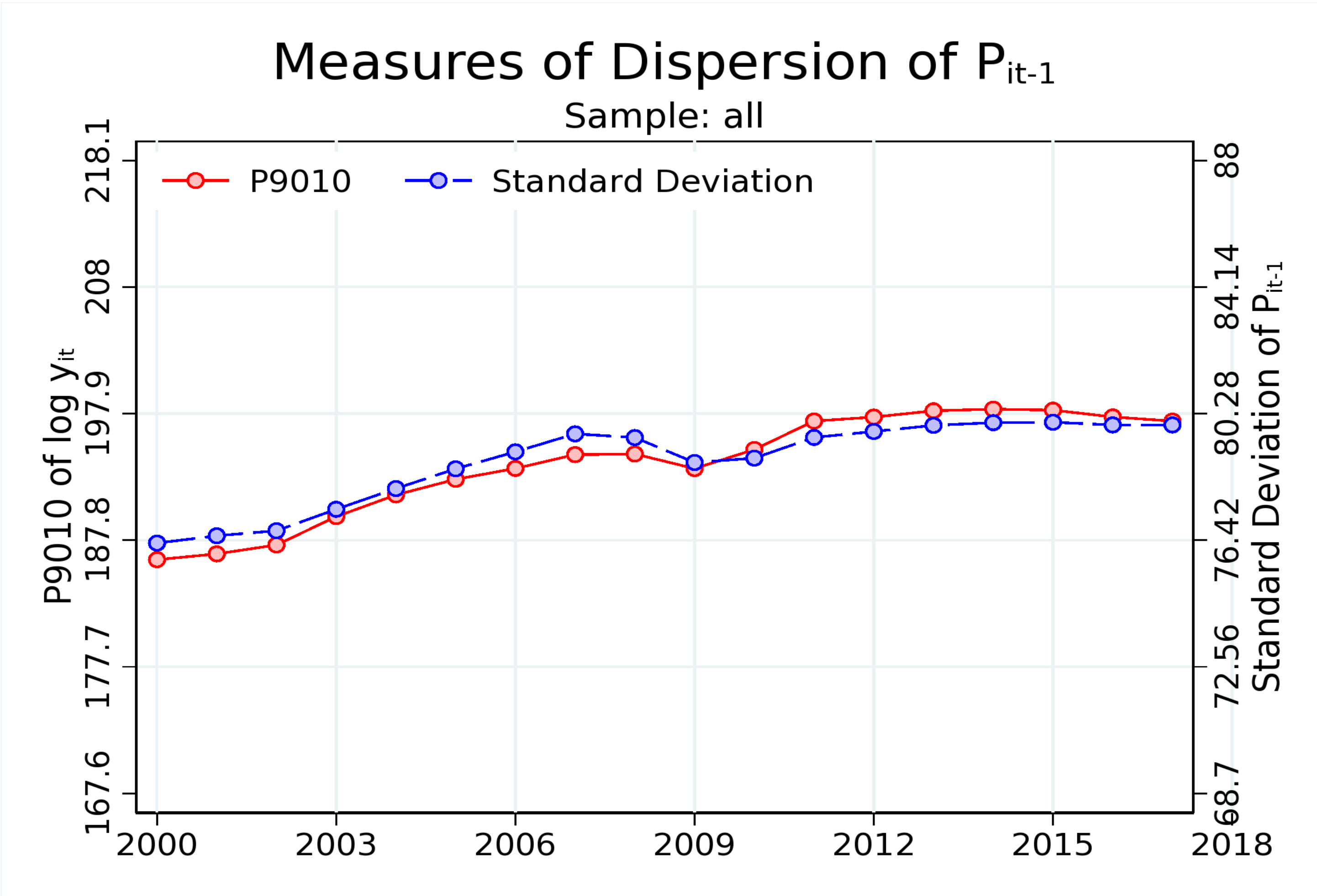
Notes: Calculations are based on the 1.8 billion person-year records in sample 1. P is average real (2018 PCE) annual earnings in years t-2, t-1 and t. The worker must have earnings above 260* federal minimum wage in at least two years to be inlcuded. The y-axis shows the difference in log real permanent earnings between the current year and the base year (1998) multiplied by 100.

Figure 3: Log Real Annual Earnings P90/P10 by Year



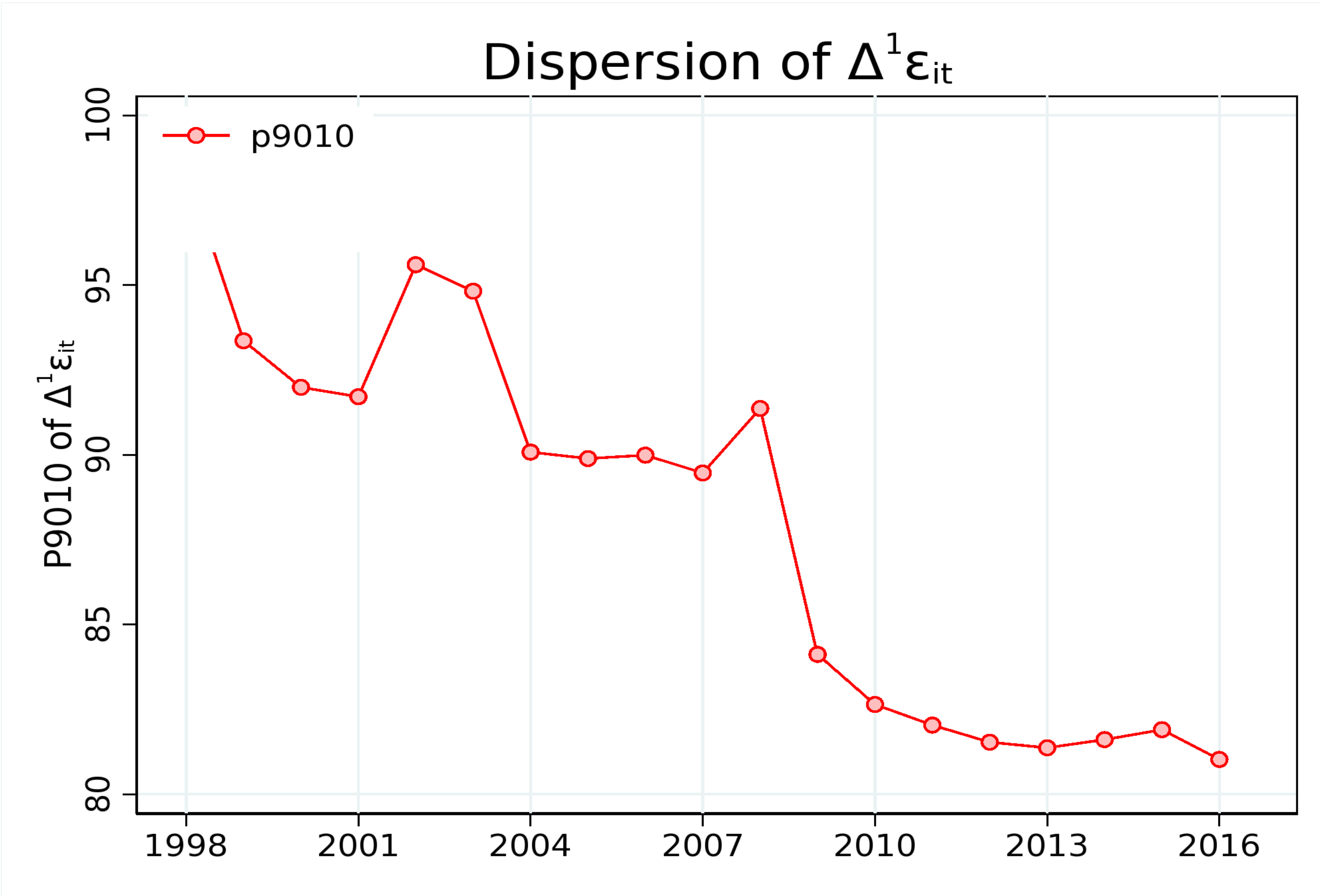
Notes: Calculations are based on the 1.8 billion person-year records in sample 1. Y is annual real (2018 PCE) log earnings at all jobs. Only person-year records above 260* federal minimum wage in that year are included. The left y-axis is the P90/P10 ratio multiplied by 100. The right y-axis is the standard deviation of Y multiplied by 100.

Figure 4: Log Real Permanent Earnings P90/P10 by Year



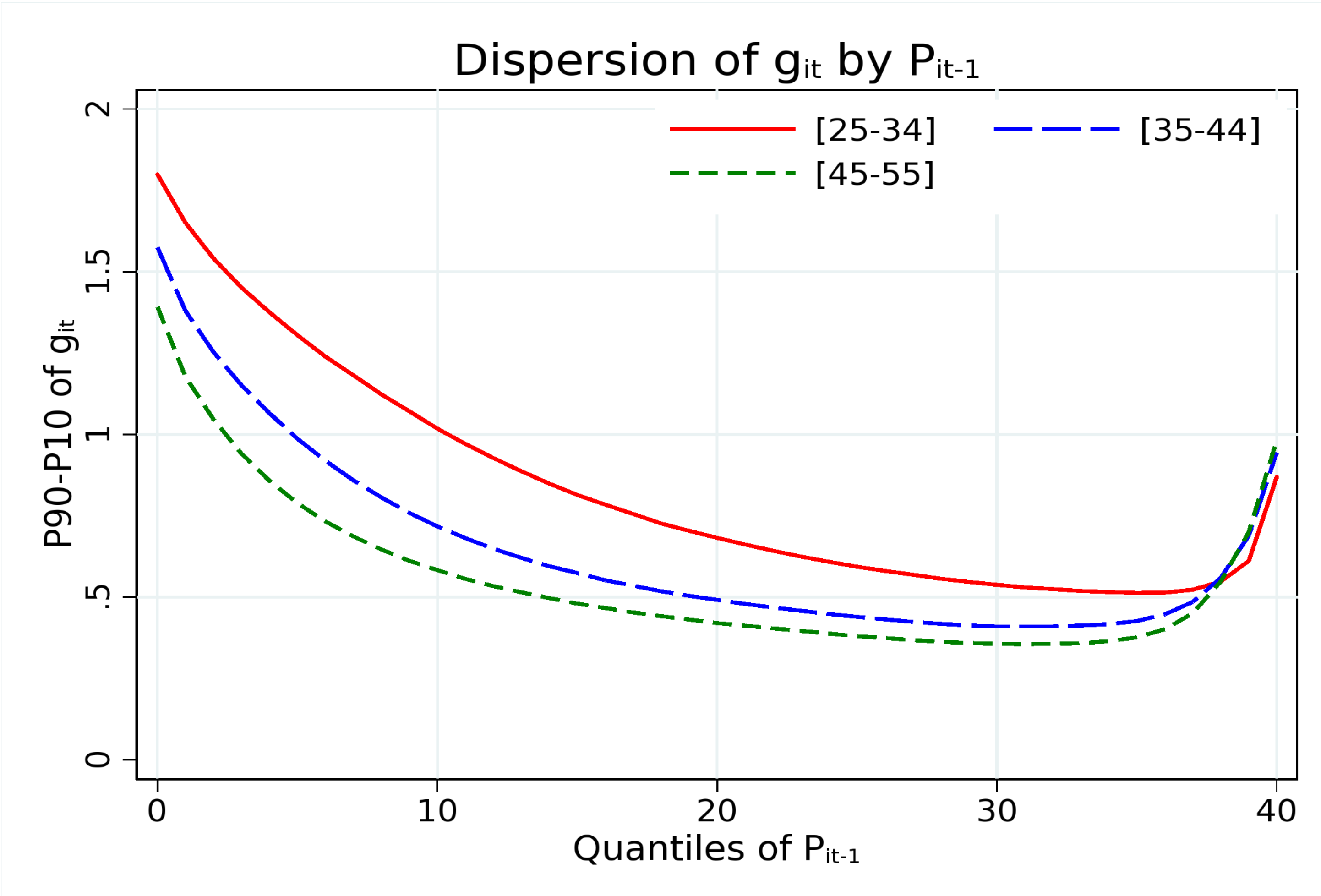
Notes: Calculations are based on the 1.8 billion person-year records in sample 1. P is average real (2018 PCE) annual earnings in t-2, t-1 and t. The worker must have earnings above 260* federal minimum wage in at least two years to be inlcuded. The left y-axis is the P90/P10 ratio multiplied by 100. The right y-axis is the standard deviation of P multiplied by 100.

Figure 5: Dispersion in the Year-to-Year Change in Age Adjusted Log Real Annual Earnings



Notes: Calculations are based on the 1.8 billion person-year records in sample 1. Delta 1 epsilon is the difference in age adjusted log real (2018 PCE) annual earnings between the subsequent and the current year. The y-axis shows the P90/P10 ratio multiplied by 100.

Figure 6: Dispersion in Annual Earnings Changes by Age and Permanent Earnings



Notes: Calculations are based on the 1.8 billion person-year records in sample 1. G is the difference in age adjusted log real (2018 PCE) annual earnings between the subsequent and the current year. The y-axis shows the P90/P10 ratio of g. P is average annual real earnings in t-2, t-1 and t. The worker must have earnings above 260* federal minimum wage in at least two years to be inlcuded. The x-axis shows the support of P divided divided into 41 consecutive non-overlapping earnings bins, with each bin representing approximately 2.5% of the earnings observations.

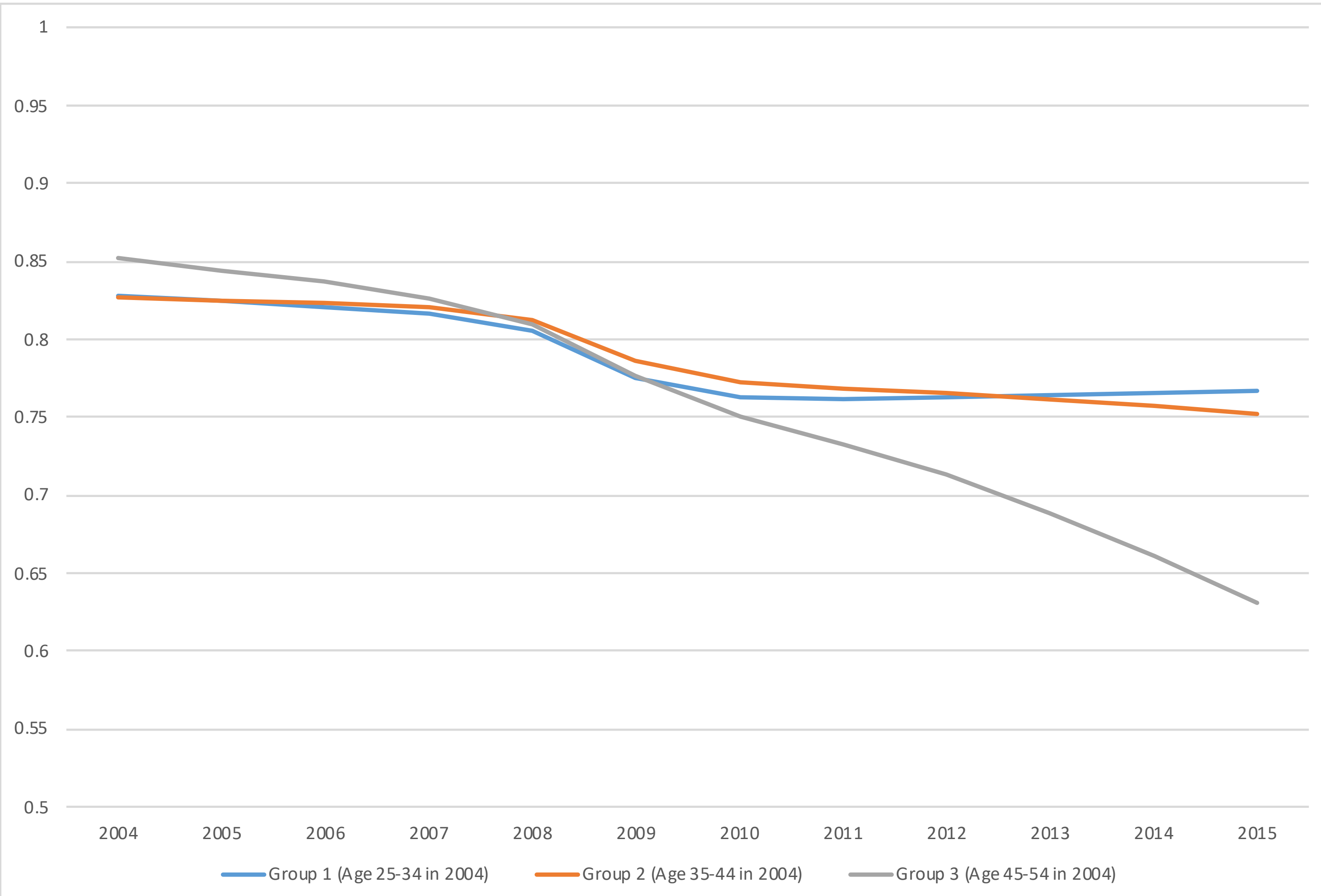
Figure 7: Permanent Income Mobility from 2000 to 2005

Notes: Calculations are based on the 1.8 billion person-year records in sample 1. P3 is the avearge of the previous, current, and subsequent years real (2018 PCE) earnings, including zero earning years. The earnings observations are ranked by dividing the support of P3 into 40 consecutive non-overlapping earnings bins each year, with each bin representing approximately 2.5% of the earnings observations. The x axis shows the earnings rank in year 2000 and the y axis shows the earnings rank in year 2005.

Figure 8: Permanent Income Mobility from 2000 to 2010

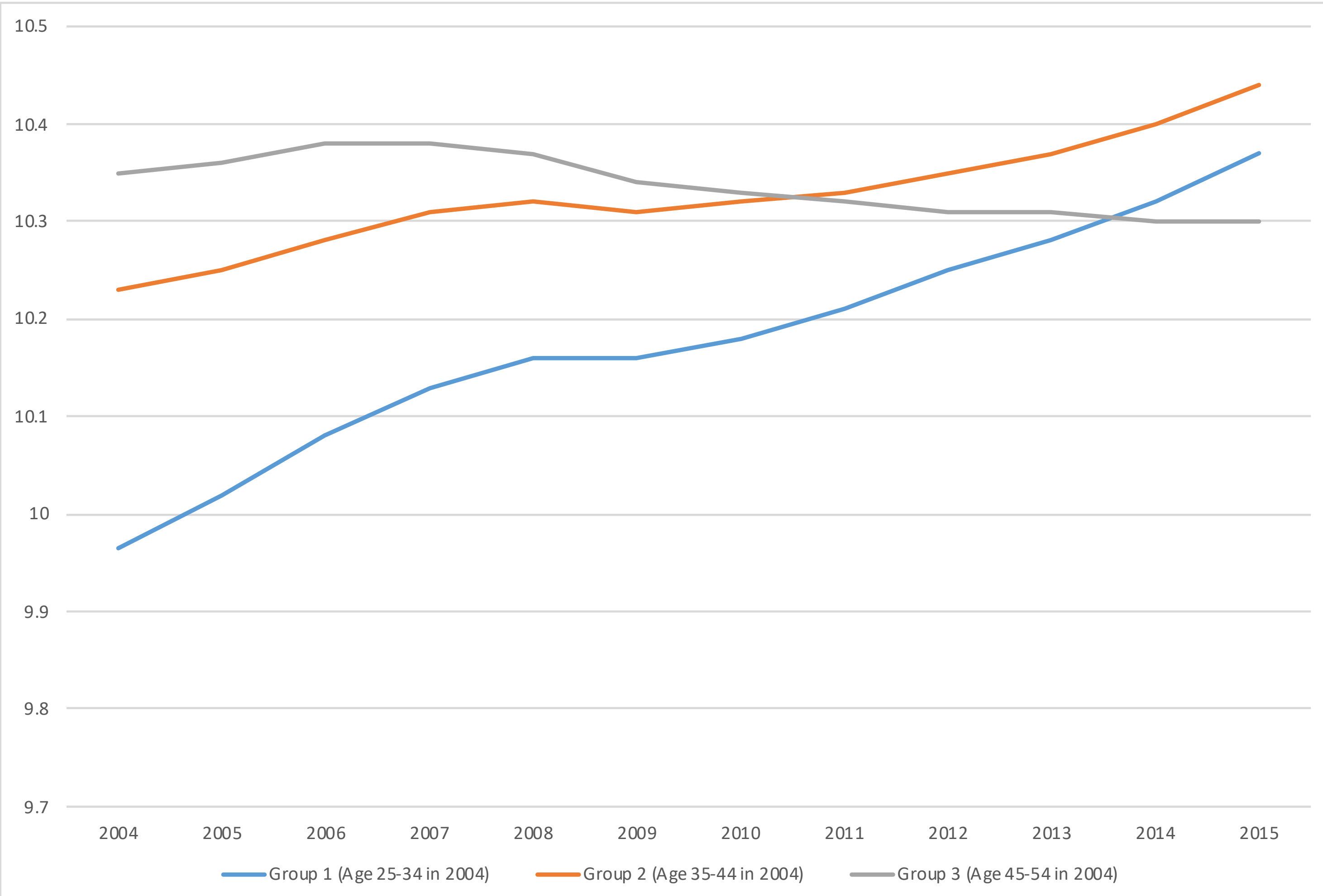
Notes: Calculations are based on the 1.8 billion person-year records in sample 1. P3 is the avearge of the previous, current, and subsequent years real (2018 PCE) earnings, including zero earning years. The earnings observations are ranked by dividing the support of P3 into 40 consecutive non-overlapping earnings bins each year, with each bin representing approximately 2.5% of the earnings observations. The x axis shows the earnings rank in year 2000 and the y axis shows the earnings rank in year 2010.

Figure 9: Percent Active in Sample 2 by Age Group and Year



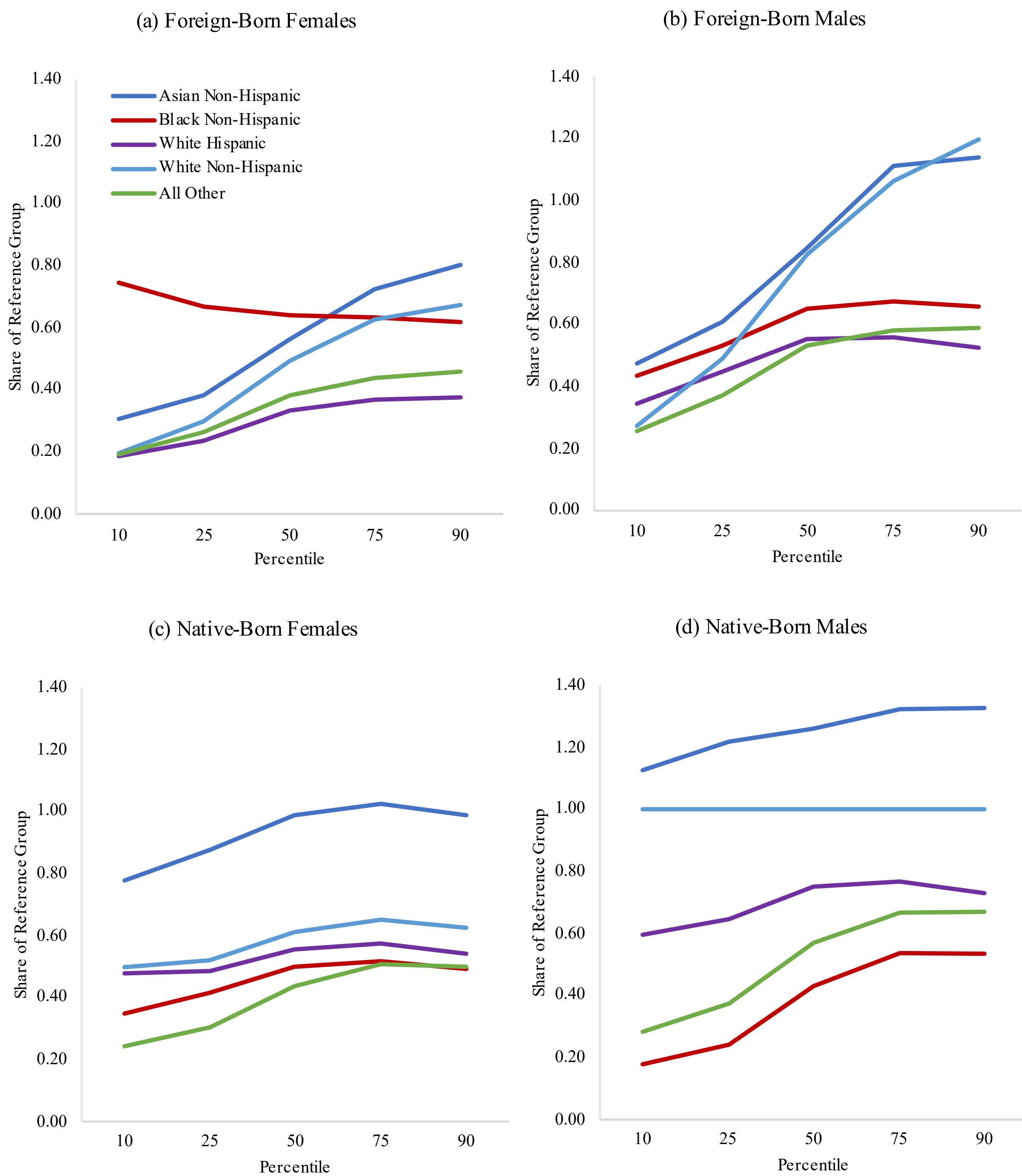
Notes: Calculations are based on the 1.3 billion person-year records in sample 2. A worker is active if they have positive earnings in at least 1 quarter during the year.

Figure 10: Mean Log Real Annual Earnings by Age Group and Year



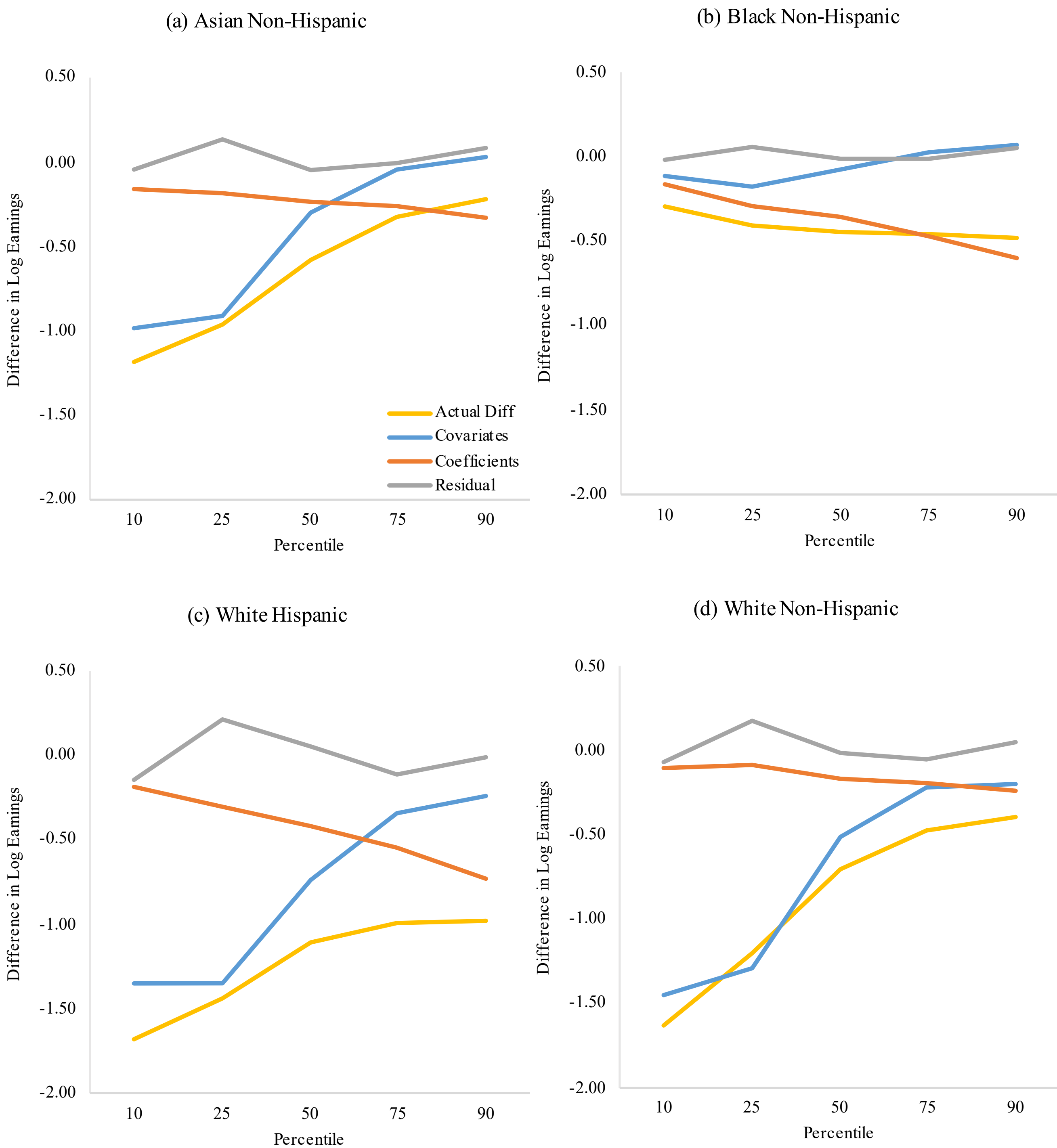
Notes: Calculations are based on the 1.3 billion person -year records in sample 2. Log real (2010 PCE) annual earnings at all jobs. To be included in a given year's estimates, the worker must have at least 1 quarter of positive earnings.

Figure 11: Log Real Average Annual Earnings as a Share of the Reference Group



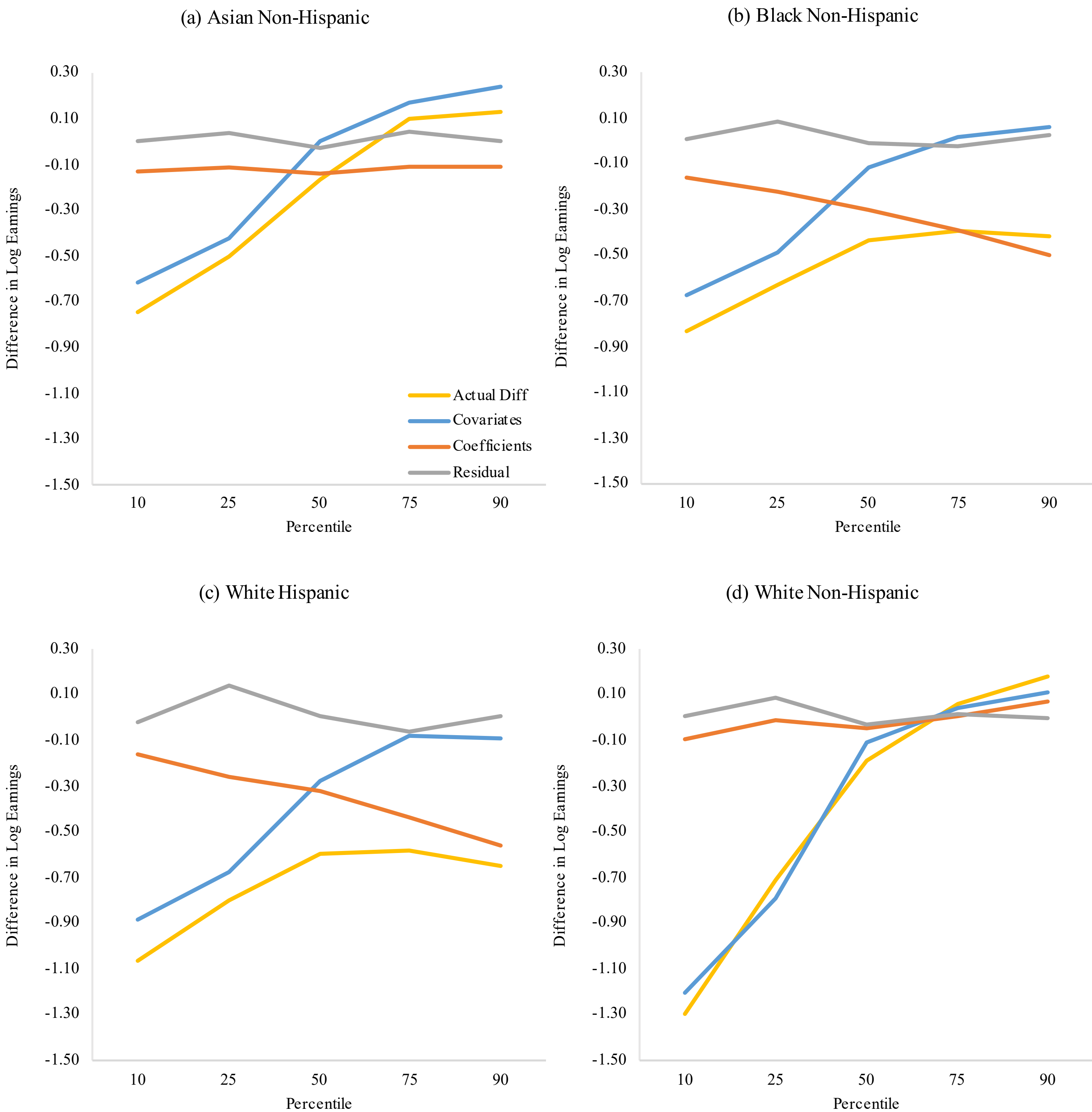
Notes: Calculations are based on the 108,800,000 worker records in sample 2. Log real (2010 PCE) average annual earnings by demographic group expressed as a share of reference group earnings (native-born White Non-Hispanic males). See text for data and estimation details.

Figure 12: Earnings Decomposition by Demographic Group (Foreign-Born Females)



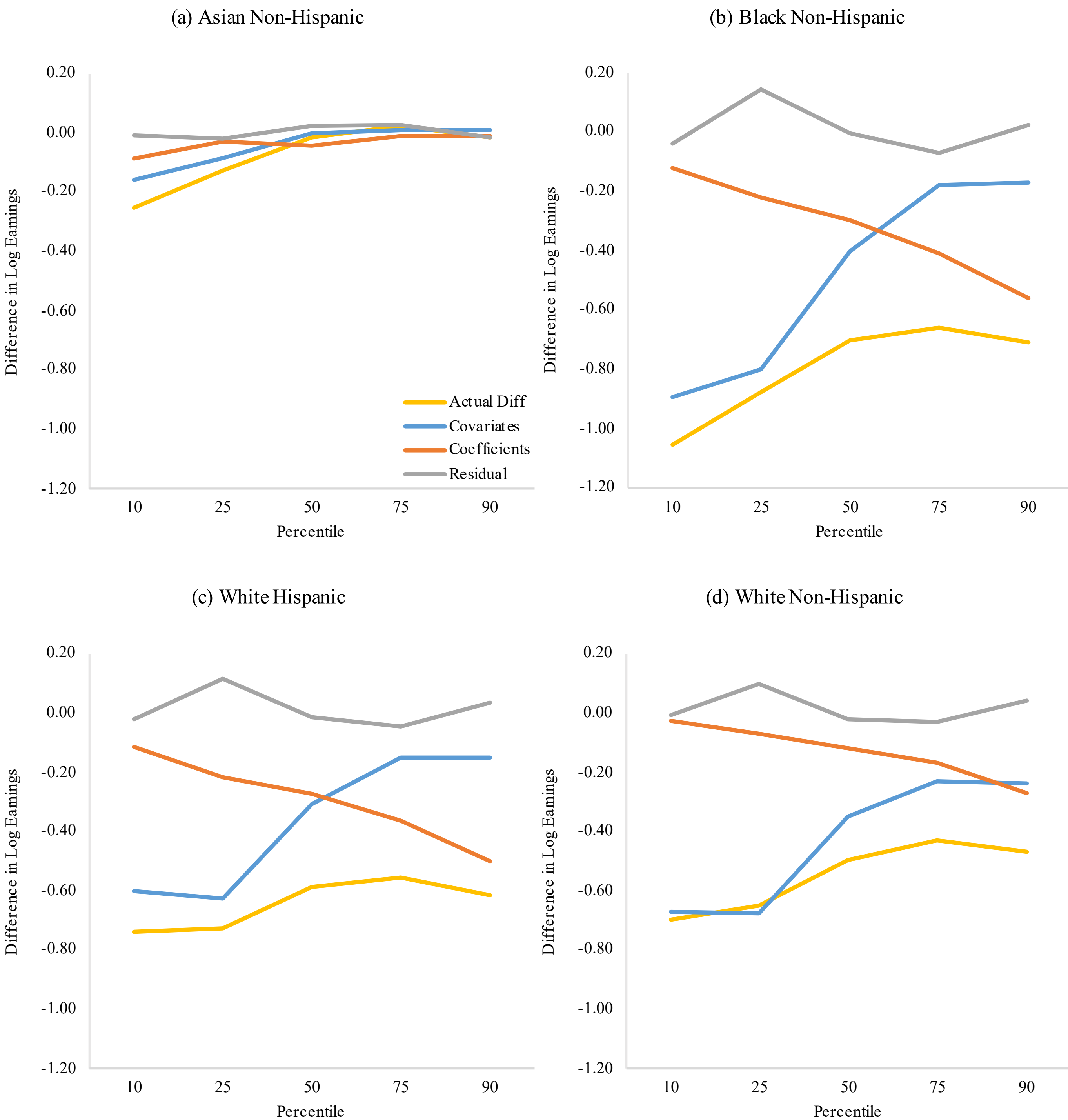
Notes: Calculations are based on the 108,800,000 worker records in sample 2. Each panel shows the actual difference in log real (2010 PCE) average annual earnings and the components for decomposition method #1 by demographic group. The reference group is native-born White Non-Hispanic males. Actual Diff = Covariates + Coefficients + Residual. See text for data and estimation details. The all other race group is in Figure 16.

Figure 13: Earnings Decomposition by Demographic Group (Foreign-Born Males)



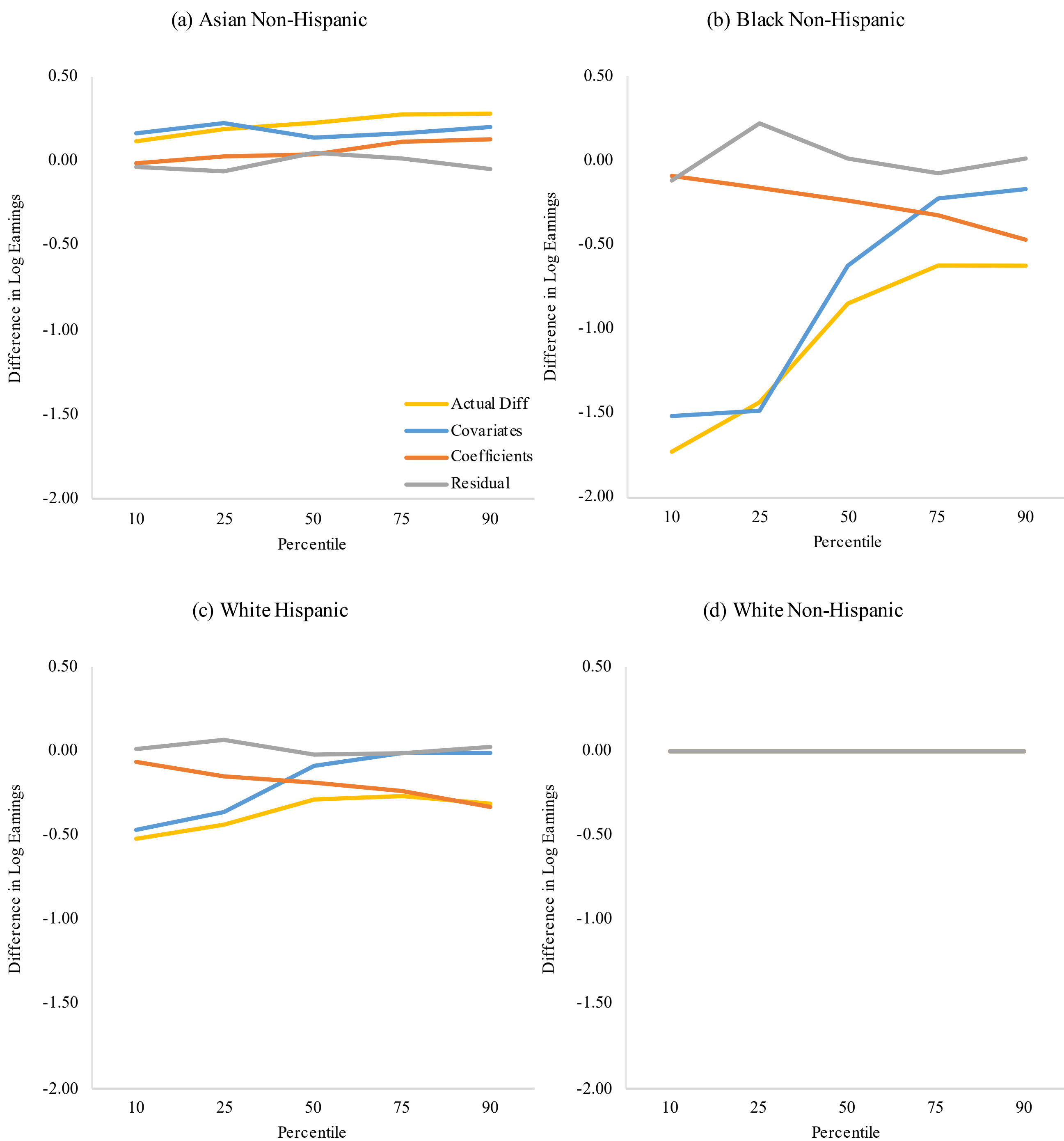
Notes: Calculations are based on the 108,800,000 worker records in sample 2. Each panel shows the actual difference in log real (2010 PCE) average annual earnings and the components for decomposition method #1 by demographic group. The reference group is native-born White Non-Hispanic males. Actual Diff = Covariates + Coefficients + Residual. See text for data and estimation details. The all other race group is in Figure 16.

Figure 14: Earnings Decomposition by Demographic Group (Native-Born Females)



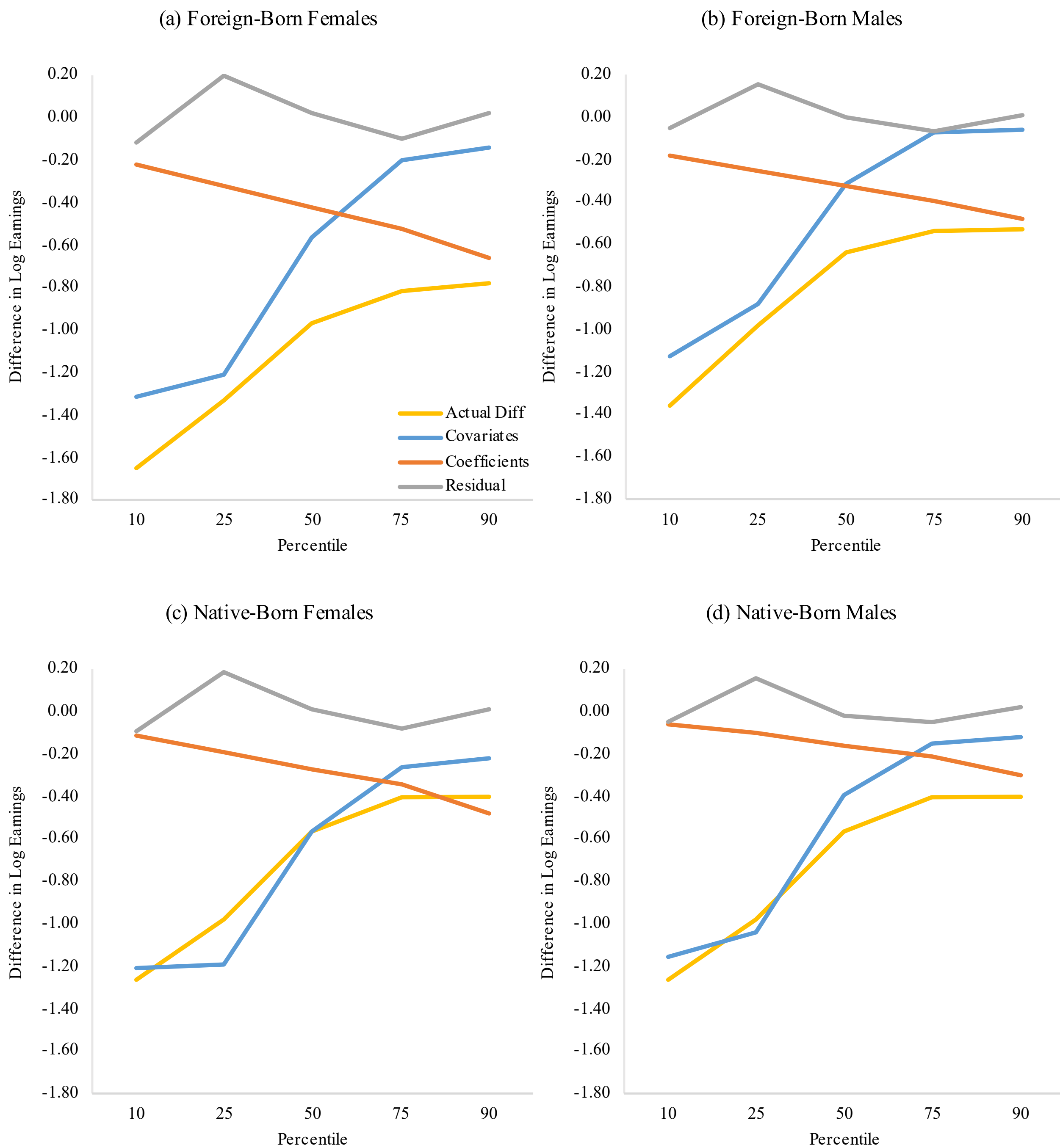
Notes: Calculations are based on the 108,800,000 worker records in sample 2. Each panel shows the actual difference in log real (2010 PCE) average annual earnings and the components for decomposition method #1 by demographic group. The reference group is native-born White Non-Hispanic males. Actual Diff = Covariates + Coefficients + Residual. See text for data and estimation details. The all other race group is in Figure 16.

Figure 15: Earnings Decomposition by Demographic Group (Native-Born Males)



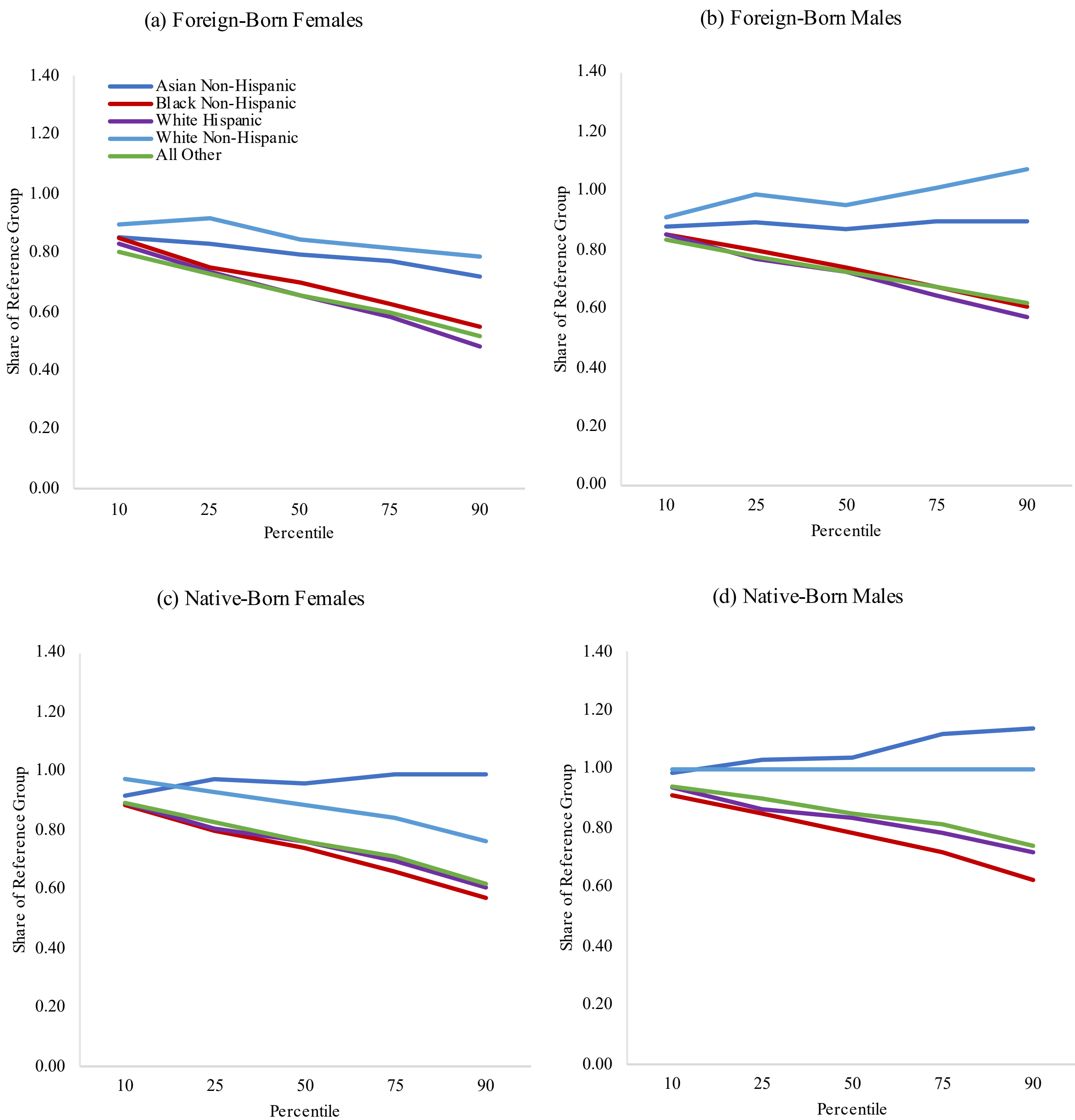
Notes: Calculations are based on the 108,800,000 worker records in sample 2. Each panel shows the actual difference in log real (2010 PCE) average annual earnings and the components for decomposition method #1 by demographic group. The reference group is native-born White Non-Hispanic males. Actual Diff = Covariates + Coefficients + Residual. See text for data and estimation details. The all other race group is in Figure 16.

Figure 16: Earnings Decomposition for All Other Races



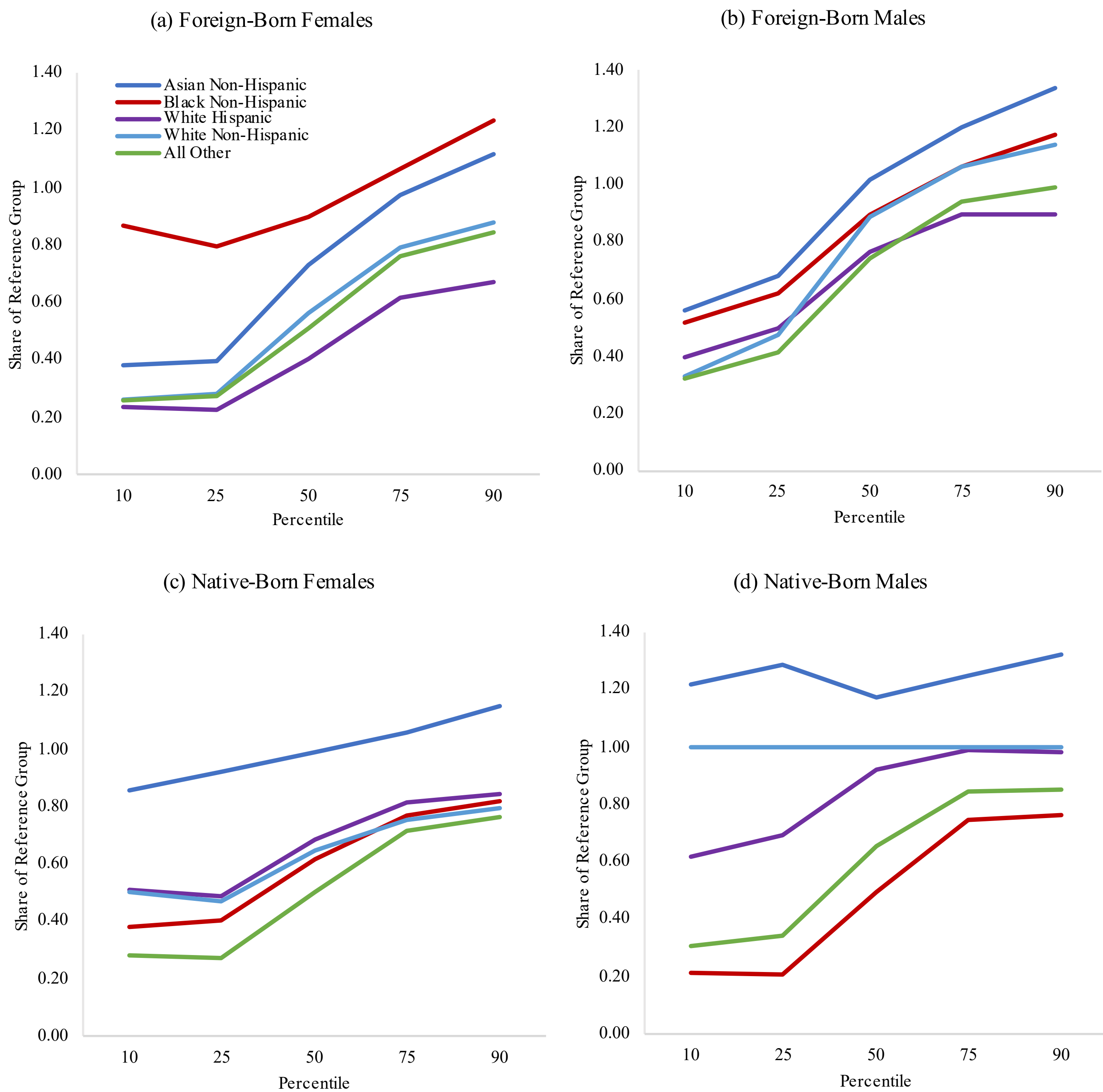
Notes: Calculations are based on the 108,800,000 worker records in sample 2. Each panel shows the actual difference in log real (2010 PCE) average annual earnings and the components for decomposition method #1 by demographic group. The reference group is native-born White Non-Hispanic males. Actual Diff = Covariates + Coefficients + Residual. See text for data and estimation details.

Figure 17: Counterfactual Earnings Differentials with Reference Group Characteristics



Notes: Calculations are based on the 108,800,000 worker records in sample 2. Each panel is based on the counterfactual log real (2010 PCE) average earnings of demographic group g with the characteristics of the reference group (native-born White Non-Hispanic males). The y-axis shows the share of reference group earnings. The actual share of reference groups earnings is shown in Figure 11. See text for estimation details.

Figure 18: Counterfactual Earnings Differentials with Reference Group Coefficients



Notes: Calculations are based on the 108,800,000 worker records in sample 2. Each panel is based on the counterfactual log real (2010 PCE) average earnings of demographic group g with the coefficients of the reference group (native-born White Non-Hispanic males). The y-axis shows the share of reference group earnings. The actual share of reference groups earnings is shown in Figure 11. See text for estimation details.

Table A1 - Age by Years in Sample 2

Years in Sample 2 / Calendar Year											
1 2004	2 2005	3 2006	4 2007	5 2008	6 2009	7 2010	8 2011	9 2012	10 2013	11 2014	12 2015
25	26	27	28	29	30	31	32	33	34	35	36
26	27	28	29	30	31	32	33	34	35	36	37
27	28	29	30	31	32	33	34	35	36	37	38
28	29	30	31	32	33	34	35	36	37	38	39
29	30	31	32	33	34	35	36	37	38	39	40
30	31	32	33	34	35	36	37	38	39	40	41
31	32	33	34	35	36	37	38	39	40	41	42
32	33	34	35	36	37	38	39	40	41	42	43
33	34	35	36	37	38	39	40	41	42	43	44
34	35	36	37	38	39	40	41	42	43	44	45
35	36	37	38	39	40	41	42	43	44	45	46
36	37	38	39	40	41	42	43	44	45	46	47
37	38	39	40	41	42	43	44	45	46	47	48
38	39	40	41	42	43	44	45	46	47	48	49
39	40	41	42	43	44	45	46	47	48	49	50
40	41	42	43	44	45	46	47	48	49	50	51
41	42	43	44	45	46	47	48	49	50	51	52
42	43	44	45	46	47	48	49	50	51	52	53
43	44	45	46	47	48	49	50	51	52	53	54
44	45	46	47	48	49	50	51	52	53	54	55
45	46	47	48	49	50	51	52	53	54	55	56
46	47	48	49	50	51	52	53	54	55	56	57
47	48	49	50	51	52	53	54	55	56	57	58
48	49	50	51	52	53	54	55	56	57	58	59
49	50	51	52	53	54	55	56	57	58	59	60
50	51	52	53	54	55	56	57	58	59	60	61
51	52	53	54	55	56	57	58	59	60	61	62
52	53	54	55	56	57	58	59	60	61	62	63
53	54	55	56	57	58	59	60	61	62	63	64
54	55	56	57	58	59	60	61	62	63	64	65

Table A2: Geography Division and Industry Definitions

Census Geography Divisions		
Number	Name	States
1	New England	CT,ME,MA,NH,RI,VT
2	Middle Atlantic	NJ,NY,PA
3	East North Central	IN,IL,MI,OH,WI
4	West North Central	IA,KS,MN,MO,NE,ND,SD
5	South Atlantic	DL,DC,FL,GA,MD,NC,SC,VA,WV
6	East South Central	AL,KY,MS,TN
7	West South Central	AR,LA,OK,TX
8	Mountain	AZ,CO,ID,NM,MT,UT,NV,WY
9	Pacific	AK,CA,HI,OR,WA

Industry Sectors		
Abbreviation	NAICS 2017 Code	Name
A	11	Agriculture, Forestry, Fishing and Hunting
B	21	Mining, Quarrying, and Oil and Gas Extraction
C	22	Utilities
D	23	Construction
E	31-33	Manufacturing
F	42	Wholesale Trade
G	44-45	Retail Trade
H	48-49	Transportation and Warehousing
I	51	Information
J	52	Finance and Insurance
K	53	Real Estate and Rental and Leasing
L	54	Professional, Scientific, and Technical Services
M	55	Management of Companies and Enterprises
N	56	Administrative and Support and Waste Management and Remediation Services
O	61	Educational Services
P	62	Health Care and Social Assistance
Q	71	Arts, Entertainment, and Recreation
R	72	Accomotation and Food Services
S	81	Other Services (exc. Public Administration)
T	92	Public Administration

Figure A1: Census Geography Regions and Divisions